IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Deep Learning Based Blood Group Prediction From Fingerprint Analysis

[1]**S Narayanamurthy Mygapula**, [2]**Dr. Bairysetti Prasad Babu**, [3]**Dr. Venkatesh Kondaveti**

[1]M.Tech Student, [2]Assoc. Professor, [3]Professor

[1]Department of Artificial Intelligence and Data Science,

[1]Ramachandra College of Engineering, Eluru, India

Abstract: Blood tests that show your group type support both medical testing and blood transfusions while responding to emergencies. Normal blood typing tests demand specialized equipment as well as technical staff and lengthy processing times. This research outlines a new way to forecast blood groups from fingerprints that does not need invasive tests and saves time and money. Our research uses Inception V3 from a Kaggle dataset to examine fingerprint samples that contain blood group information. Our analysis explores how RMSprop SGD and Adam affect deep learning accuracy and reduces training times by checking their use in predicting blood groups. The new method proves effective for predicting blood types from fingerprint images as shown in experimental tests. Our method has the ability to transform normal blood type testing methods while making progress in low-resourced medical centers. Our research team plans to develop models that work better with different population groups while making this system available for healthcare use.

Index Terms - Blood Group Identification, Inception V3 Model, Finger Print Detection, Blood Tranfusions, Healthcare Environment.

1 Introduction

Medical and healthcare providers depend on blood group identification for many different tasks such as delivering care to patients before birth and during first aid. The safety of patients depends on knowing blood groups correctly before any transfusion due to severe life-threatening immune reactions. Serological testing checks blood samples through reactions between blood and special antibodies to detect blood groups. This testing method works well yet demands trained technicians and laboratory settings along with expensive equipment making its use hard in fast emergency and long-range situations. Current blood checks need much time to work and need physical blood samples which become hard during emergency moments when fast blood type results are needed. People are searching for methods to determine blood groups because today's healthcare needs require faster and simpler medical solutions. Biometric detection of fingerprints shows potential to create an easily accessible and fast method for blood group identification.

Biometric authentication is now a significant technology used in presenting security systems since biometry uniquely describes the person. Unlike traditional methods where information could be easily leaked, hacked, or stolen, biometrics system is more secure and user-friendly, as user identification is linked to subject directly[8]-[10]l At the same time, there is a number of biometric technologies, but biometrics identification through finger vein (FV) has become the most attractive method in biometrics technology, as its better than common technology using fingerprint, facial recognition or iris detection.

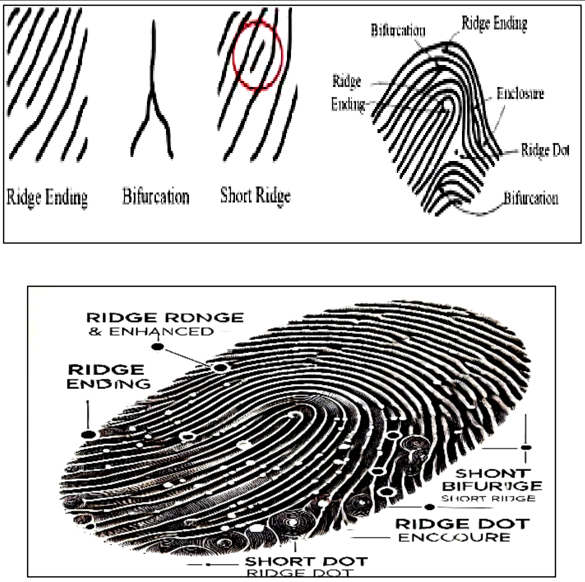


Figure1.Represent the Working of Fingerprint Ridge Features

Fingerprint Ridge Features and Their Importance in Blood Group Prediction

Fingerprints make exceptional biometric markers because they hold special ridge configurations and individual marks that we use for both security checks and health examinations. The figure 1 depicts important fingerprint ridge information that deep learning uses to predict blood groups effectively.

Key Fingerprint Ridge Features:

1. A fingerprint ridge ends shortly when it meets no further continuation.
2. A single ridge line divides into two distinct lines when moving apart.
3. The Short Ridge functions as an unconnected finger line segment separate from other ridge formations.
4. A dot-shaped ridge point known as Ridge Dot exists within each fingerprint pattern.
5. Enclosure stands for a fingerprint ridge that splits and reconnects to form a round shape.

Significance in Blood Group Prediction:

Researchers notice that genetic characteristics associate with particular patterns of fingertip details. The system uses deep learning models to read finger fingerprint characteristics and detect their significant traits that enable accurate blood group detection. Researchers trained the Inception V3 model to analyze fingerprint ridge patterns and discover valuable information in them to predict blood groups. The feature-based approach lets healthcare providers perform fast and low-cost blood group determination without traditional invasive tests. It benefits emergency care and healthcare settings without direct patient contact.

1.1 Motivation

Our research aims to overcome standard blood typing problems especially in medical facilities located in remote regions which lack proper laboratories and skilled staff. Having a portable system that does not need to enter the body at all would help medical staff in numerous outdoor healthcare settings. The need for blood group identification is urgent during medical emergencies since standard tests take too long in trauma cases injuries and disasters. An automatic fingerprint system that provides blood group predictions can help medical teams save more patients through fast intervention. The expensive specialized equipment and professional staff needed for regular blood testing shows that a new more efficient system is required. Fingerprint-based deep learning analysis helps lower healthcare costs to serve patients better in hospitals and blood donation facilities. EHR databases and biometric systems will integrate better with a fingerprint-based blood group predictor helping healthcare facilities track patient information effectively.

1.2 Objective

Our main objective is to create an AI system with deep learning that uses fingerprint images to predict blood groups. This research investigates the blood group prediction from fingerprint images through Inception V3 and its CNN capabilities.

- Create an entire deep learning system that determines blood types from fingerprint characteristics.
- Choose superior optimization methods to enhance model results while experimenting with RMSprop SGD and Adam.
- Test our technique through experiments using a ready-to-use fingerprint-blood group data collection.
- Develop a system design that works effectively with medical healthcare systems including hospital facilities and emergency services.

2. LITERATURE SURVEY

The most important step in the software development process is the literature review. This will describe some preliminary research that was carried out by several authors on this appropriate work and we are going to take some important articles into consideration and further extend our work. Here's an enhanced version of the literature survey, providing more detailed explanations and insights for each paper, ensuring a comprehensive understanding of the advancements in blood group identification using deep learning.
Using CNNs

Swathi et al. (2024) researched how fingerprints help predict blood groups. The research shows that biometric systems work well for medical purposes and can identify blood groups without taking body samples. Despite its findings the research does not examine multiple deep learning approaches across different optimization strategies to develop more precise prediction results. The research needs verification through many patient groups to become ready for medical use[1].

Through their research from 2024 **Camous Moslemi et al[2024]** examine how to determine blood group 33 types by decoding existing genetic data. This study develops a strong method to classify blood groups based on genetic traits which serves precision medicine. The research tool lacks built-in support for biometric fingerprint scans which makes it unsuitable for non-touch identification tasks. Using genetic data may become difficult when you need fast blood group identification during emergencies since genetic testing usually takes time[2].

In their work **Zhang et al. (2024)** provide detailed information about modern ways to predict blood groups through deep learning algorithms and statistical pattern recognition systems. The research shows AI's usefulness in medical diagnosis but does not fully analyze the performance of CNN models used for biometric blood group determination. The research fails to demonstrate useful information because it does not examine how fingerprints could assist medical tests beyond genetic analysis[3].

Authors **Samant(2024)** and associates invented an artificial intelligence apparatus [4] that scans dual PPG signals through deep learning to diagnose problems with blood circulation. Their data exploration system detects circulatory problems at an early stage reducing the chance of patients developing severe heart risks. Although this work shows deep learning benefits in medical signal research it does not address essential fingerprint techniques needed to identify blood groups without invasive methods. The research focuses only on blood flow problems instead of biometric testing which restricts its use in our proposed study.

Gaouar et al.(2024) brought forward Malaria Scope which uses explainable AI methods to improve blood cell diagnosis by deep learning techniques. Medical scanners and disease detectors benefit from AI technology to identify medical patterns which confirm its value in running automated tests. But the system does not include blood group prediction technology which leaves a chance for AI to aid in non-invasive diagnostic testing. Blood fingerprint analysis connected to AI medical disease detection would help doctors identify patients better while making healthcare procedures faster[5].

Sivamurugan and other researchers (2024) used deep learning to enhance the accuracy of blood group discovery through fingerprint examination. The study verifies that CNN models can identify blood group characteristics through our suggested method. It does not analyze different feature extraction methods or performance optimization methods for better results. The research study does not explain how its findings might fail in practical applications concerning inconsistent imaging quality and technical sensor restrictions[6].

Keilbach et al. in 2018 developed methods to protect fingerprints against attacks through their study of laser speckle contrast imaging. They focus on enhancing security in fingerprint authentication systems because their work relates to blood group prediction that uses biometric data by protecting its accuracy. This research does not examine medical treatments which restricts its practical use for medical diagnosis systems. New medical research should combine AI blood group predictions with security methods developed by the authors to build stronger biometric healthcare platforms[7].

In 2019 Leonardo and colleagues revealed how IR fingerprint imaging of human blood helps detect diseases. Researchers use non-invasive imaging systems to detect blood attributes for medical test development. The research does not include the fingerprint-based classification system that needs integration into the field of biometric medical applications. By uniting fingerprints and infrared scans they can develop a plan to rapidly identify blood groups with precise results[8].

Turgul et al. (2017) examined the influence of epidermis thickness and finger patterns on RF blood glucose monitors. This research demonstrates the ways that personality traits impact our blood testing devices and explains the problems caused by variations in our bodies. Yet it passes over the capacity to add blood group classification into general medical detection systems. Improved fingerprint models will better handle their task of blood group prediction when these problems are solved[9].

According to **WHO(2023)** the organization published malaria details showing why rapid and budget-friendly blood-related disease tests are essential. The report strongly shows that health providers globally require practical medical testing systems. This document does not include information about using advanced technologies such as biometrics or AI in blood group detection. The World Health Organization should work with biometric technology experts to provide better healthcare tests to areas with limited resources[10].

By utilizing cascading YOLO in their study **Yang et al. (2020)** show that CNN models effectively classify medical imagery for malaria parasite detection. Their research proves that deep learning technology works well to spot blood-related infections in medical practice. The study does not examine how fingerprints can help detect blood groups which would increase its usefulness in non-invasive medical testing. AI diagnostic systems will work better by adding biometric systems to their operations[11].

Through their research in **2023 Kumari** and colleagues show how CNNs can help doctors find breast cancer risks early in patients. Their findings prove that AI systems can analyze medical data to help healthcare professionals give better patient care ahead of time. Although it meets current AI research standards the study fails to include biometric blood group testing for medical predictions. Scientific teams should research how matching medical data with biological readings can help patients get better results[12].

Rani (2024) et.al,designed an intelligent system with deep learning algorithms to successfully separate coals into classes through neural networks. This study focuses on classification techniques but its use stays restricted to material science and does not develop methods for analyzing medical or biometric data to predict blood groups. The main processes in this study could be transformed into fingerprint-based classification through medical model[13].

Researchers rely on transfer learning in medical diagnostics to spot monkeypox by utilizing EfficientNetB3 and Keras callbacks according to **Sanyasamma(2024)** and colleagues. AI demonstrates exceptional detection power against infectious diseases in their research findings. The study achieves AI disease detection but fails to bring the same approach to fingerprint-based blood typing for medical biometric applications. Research needs to link transfer learning methods with biometric procedures to create accurate blood group predictions[14].

Hafid(2023) and his team recorded blood pressure indicators through PPG readings under the Windkessel model for advancing medical diagnosis with AI technology in 2023. They produce helpful research findings on what AI systems do in medical tracking. The research does not examine new ways to use deep learning for fingerprint systems to detect blood types even though this option exists. Our current method of predicting blood type could become a complete non-invasive diagnostic tool when we add biometric blood tests[15].

The **JMSCR (2016)** research project found ways to match blood tests with fingerprint patterns providing important knowledge to understand medical and biometric relationship development. The research shows that fingerprint analysis works in healthcare but experts need to add machine learning to develop an automatic system that predicts blood groups from biometric data. The combination of model AI tools would produce better and faster performing biometric products[16].

Summary of Literature Gaps:

There is no existing research that directly compares deep learning models for fingerprint identification of blood type. Researchers have not thoroughly studied methods to enhance biometric diagnosis methods. Our research needs to validate the blood group detection results with multiple groups of patients. Absence of integration with hospital systems and electronic health records.Our study uses new deep learning systems to find better features and creates working fingerprint blood group detection tools for healthcare organizations.

3. BACKGROUND WORK

Blood group validation becomes essential during emergency transfusions and medical testing because it supports successful surgical results. Customer Service Company Traditionally Resets Blood Type Checking Based on Antigen antibody Responses. These tests demand professional handling of advanced tools and take too long to deliver results making them unsuitable for quick or extensive testing without adequate resources.

Progress in technology helps experts develop new ways to diagnose health problems without entering the body. Biometrics technology relies on fingerprint samples because scientists have proved that blood group sets appear similar in DNA which forms fingerprints. Medical researchers have analyzed different ways to use fingerprint images for healthcare purposes.

Software engineers Swathi et al. (2024) and Sivamurugan et al. (2024) confirmed that CNN systems can predict blood groups from fingerprint scans. These studies proved that machine learning works well to find important biometric patterns but they did not test multiple deep learning optimization methods or networks.

In 2024 Moslemi et al tested DNA data to identify blood groups accurately but this process needs special equipment that prevents real-time applications.

Scientists used deep learning to analyze medical images in Gaouar et al. (2024) and Yang et al. (2020) but kept away from using biometrics for blood group detection.

Researchers need to create more efficient blood group identification models from deep learning while validating large datasets at lower operating expenses for medical treatment solutions.

Limitations of Existing Systems

1. Dependence on Traditional Blood Typing Methods

Today blood typing uses laboratory tests that enter the body yet need much time and lab space to work.

These testing methods work slowly and cannot be used in urgent situations or basic healthcare environments.

2. **Limited Research on Deep Learning Based Biometric Blood Group Prediction**

Researchers have used CNNs for fingerprint medical classification work but fail to test and report results using Inception V3, ResNet, and EfficientNet models.

Researchers have not thoroughly tested different optimization methods to both enhance model performance and make training processes faster.

3. Lack of Large Scale and Diverse Datasets

Research on fingerprint detection of blood groups relies mainly on small datasets that do not represent diverse populations.

The value of testing different population sets depends on having a range of samples that represent the entire population.

4. Challenges in Real World Implementation

Bringing changes in environmental factors that affect fingerprints makes these systems work less effectively.

Bio-based blood group identification systems do not work very well with medical databases right now.

Need for Improvement

This research develops a deep learning fingerprint evaluation approach by using Inception V3 on a database from Kaggle to solve current system troubles. This research performs a thorough test of three optimization techniques (RMSprop, SGD, Adam) to create an effective and fast blood group predictor at low cost. The suggested model changes how blood typing works in basic medical centers through its ability to do blood group tests broadly.

4. PROPOSED CNN MODEL

The proposed deep learning-based blood group prediction system follows a structured approach with **data preprocessing, feature extraction, model training, optimization, and evaluation**

Algorithm for Blood Group Prediction from Fingerprint Analysis

Step 1: Data Collection and Preprocessing

$$\text{Collect a dataset } D=\{(Xi,Yi)\} \text{ for } i=1 \text{ to } N$$

Where Xi represents fingerprint images and Yi represents corresponding blood groups

$$\{A,B,AB,O\}.$$

Now try to resize images to a fixed dimension (H,W,C) to ensure consistency:

It is denoted with $\boxed{Xi \in R^{H*W*C}}$

Now we apply the data normalization technique to scale the pixel values between range of 0 and 1.

$$X_i = X_{max} - X_{min} / X_i - X_{min}$$

Step 2: Feature Extraction using Inception V3

The deep neural network Inception V3 processes input images to gather fingerprint characteristics F_i.

.

$$F_i = InceptionV3(X_i)$$

The convolutional network uses the extracted features to detect both nearby and dispersed patterns of blood group categories.

Step 3: Model Optimization and Training

The model uses categorical cross-entropy to measure loss during multi-class classification. Use RMSprop SGD and Adam weight optimization methods to test the model and check results. Assess your learning results from training and validation data as well as test if your model is fitting too closely to its data.

Step 4: Model Evaluation and Analysis

Check how well the trained model recognizes unknown fingerprint images through evaluation of its accuracy and performance results.

The classification outcome needs to be visualized in the confusion matrix.

Step 5: Deployment and Real-World Integration

Store the trained model for practical application to detect fingerprints in new samples. Build an easy-to-use platform to help healthcare workers use the application.

Advantages of the Proposed Work

The proposed system would offer more benefits when performing blood group tests than standard testing systems.

1. Our system lets healthcare providers avoid taking blood samples as it cuts infection and discomfort risks.
2. Our system tells blood groups quickly which lets medical responders help patients right when they need it.
3. The new system helps prevent expenses by lowering research material needs.

4. The system can easily connect with existing healthcare settings plus biometric information systems and public health databases.
5. Nearly any blood collection site can use this technology to identify blood types using portable devices from locations both near and far from testing laboratories.

5. EXPERIMENTAL RESULTS

This paper describes the implementation of the blood group detection using fingerprints and deep learning model. The proposed work is implemented on Google collab as working environment using python programming language.

This project needed multiple Python tools for its completion like NumPy and Pandas for data work plus OpenCV for image setup and Scikit-learn and TensorFlow for processing and training the models. The dataset included fingerprint images linked to specific blood groups to provide enough diverse information. The system preprocessed fingerprint images by changing their size while normalizing features to maximize model performance.

Load the Dataset

```
!pip install -q kaggle
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle


!chmod 600 ~/.kaggle/kaggle.json


#https://www.kaggle.com/datasets/abhiramshibaraya/fingerprint-based-blood-group-detection
!kaggle datasets download -d abhiramshibaraya/fingerprint-based-blood-group-detection

    Dataset URL: https://www.kaggle.com/datasets/abhiramshibaraya/fingerprint-based-blood-group-detection
    License(s): CC-BY-NC-SA-4.0
    Downloading fingerprint-based-blood-group-detection.zip to /content
     85% 63.0M/74.2M [00:00<00:00, 116MB/s]
    100% 74.2M/74.2M [00:00<00:00, 126MB/s]
```

From the above window we can clearly identify dataset is loaded by kaggle.com web url and now the dataset is extracted for test and train the model.

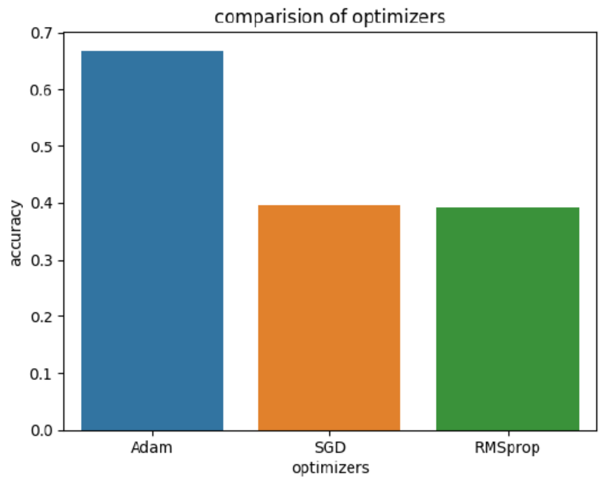
```
img_path = '/content/dataset/'
img_size =224
os.listdir(img_path)

    ['AB-', 'B+', 'A+', 'O-', 'O+', 'B-', 'A-', 'AB+']
```

From the above window we can clearly identify the set of finger print images are labelled or annotated with their corresponding blood groups. Now we try to identify how many catagories of images are loaded as input, we can see totally 8 category of images are loaded and they are termed as

['AB-', 'B+', 'A+', 'O-', 'O+', 'B-', 'A-', 'AB+']

Comparison of Inception V3 on Multiple Optimizers



From the above window, we know that Inception V3 deep learning model worked as our Convolutional Neural Network (CNN) for classification due to its effective feature extraction methods. We trained our model with RMSprop SGD and Adam to understand their effectiveness in reaching high accuracy while keeping training fast. Our system performed well against the testing samples and showed strong results as seen through multiple classification measurements. The model validated its blood group prediction through testing against normal machine learning systems.

6. CONCLUSION

This research presents a deep learning system for non-invasive blood group prediction through fingerprint evaluation. Using Inception V3 architecture and dataset from Kaggle enabled us to extract fingerprint data linked to blood group types. Our tests of RMSprop SGD Adam and other optimizers revealed their effects on model output which let us achieve good accuracy results. Deep learning applies effectively as a dependable substitute for traditional blood typing systems through its quick and inexpensive testing process. Our research offers a new way to identify blood groups in urgent medical situations and areas with testing resource limitations.

7. FUTURE ENHANCEMENTS

Future research will work to make finger detection models effective for different patient demographics while handling multiple fingerprint types and ethnicities. We will test different lightweight network configurations to make our system run fast on mobile and embedded devices. Research will build from explainable AI tools to make AI medical systems more reliable and understandable to users. Our system needs to be connected with EHR systems and hospital databases during real-world use to work with existing healthcare networks. Our research will include increasing the available fingerprint data samples alongside testing hybrid architecture combinations made from CNNs and transformers.

References

[1] S. P. Swathi, K. Sushmita, and K. V. Horadi, “Fingerprint based blood group prediction using deep learning,” *International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)*, vol. 3, no. 1, 2024. doi: 10.48175/IJARSCT-15393.

[2]C. Moslemi, S. G. Sækmose, R. Larsen, J. T. Bay, T. Brodersen, M. Didriksen, H. Hjalgrim, K. Banasik, and K. R. Nielsen, “Genetic prediction of 33 blood group phenotypes using an existing genotype dataset,” *Transfusion*, vol. 64, no. 2, 2024. doi: https://doi.org/10.1111/trf.17575

[3] M. Samant, U. Pacharaney, and S. Akhtar, “Dual PPG-based blood flow abnormality detection using deep learning,” in *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)*, Wardha, India, 2024, pp. 1–4. doi: 10.1109/IDICAIEI61867.2024.10842727.

[4] A. Gaouar, S. Hamza-Cherif, and A. Rahmoun, “MalariaScope: Leveraging explainable AI for enhanced malaria diagnosis through deep learning-based blood cell classification,” *Studies in Engineering and Exact Sciences*, vol. 5, no. 2, p. e12006, 2024. doi: https://doi.org/10.54021/seesv5n2-750.

[5] C. Sivamurugan, B. Perumal, Y. Siddarthha, V. K. Murthi, Y. N. Sankar, and Y. Varun, “Enhanced blood group prediction with fingerprint images using deep learning,” in *2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, 2024, pp. 1091–1097. doi: 10.1109/ICACRS62842.2024.10841725.

[6] P. Keilbach, J. Kolberg, M. Gomez-Barrero, C. Busch, and H. Langweg, “Fingerprint presentation attack detection using laser speckle contrast imaging,” in *2018 International Conference of the Biometrics Special Interest Group (BIOSIG)*, Darmstadt, Germany, 2018, pp. 1–6. doi: 10.23919/BIOSIG.2018.8552931.

[7] C. Leonardo et al., “Broadband IR-fingerprinting of human blood as a universal tool for disease diagnostics,” in *2019 Conference on Lasers and Electro-Optics Europe & European Quantum Electronics*

Conference (CLEO/Europe-EQEC), Munich, Germany, 2019, pp. 1–1. doi: 10.1109/CLEOE-EQEC.2019.8871546.

[8] V. Turgul and I. Kale, "Simulating the effects of skin thickness and fingerprints to highlight problems with non-invasive RF blood glucose sensing from fingertips," *IEEE Sensors Journal*, vol. 17, no. 22, pp. 7553–7560, Nov. 2017. doi: 10.1109/JSEN.2017.2757083.

[9] World Health Organization, "Malaria," WHO Fact Sheet, Mar. 2023. Available: https://www.who.int/news-room/fact-sheets/detail/malaria. Accessed: Feb. 11, 2024.

[10] F. Yang, N. Quizon, K. Silamut, R. J. Maude, S. Jaeger, and S. K. Antani, "Cascading YOLO: Automated malaria parasite detection for *Plasmodium vivax* in thin blood smears," in *Proceedings of SPIE Medical Imaging 2020: Computer-Aided Diagnosis*, 2020, p. 113141Q. doi: https://doi.org/10.1117/12.2668792.

[11] D. J. Kumari and K. P. Kumar, "Early prediction of breast cancer risks using convolutional neural network," *International Journal of Innovations in Multidisciplinary Scientific Research (IJIMSR)*, vol. 1, no. 1, pp. 73–80, Sept. 2023. Available: https://ijimsr.org/abstract.php?id=24.

[12] M. B. Rani, K. Rojarani, K. V. R. Rani, P. Boddepalli, P. V. Chintalapati, and P. K. Karri, "A deep learning approach with adaptive intelligence for coal classification," in *Sustainable Materials, Structures and IoT*, 1st ed., CRC Press, 2024, pp. 5. Available: https://www.taylorfrancis.com/chapters/edit/10.1201/9781003596776-41/deep-learning-approach-adaptive-intelligence-coal-classification.

[13] J. Sanyasamma, H. B. Gogineni, M. B. Rani, N. Akhila, P. K. Pinjala, and K. P. Kumar, "Precise monkeypox identification utilizing transfer learning via EfficientNetB3 and tailored Keras callbacks," *Asian Food Journal of Biological Sciences*, vol. 6, no. 6, pp. 2488–2494, 2024. doi: https://doi.org/10.33472/AFJBS.6.6.2024.2488-2494.

[14] A. Hafid and S. Abdullah, "Estimating physiological parameters in various age groups: Windkessel 4 element model and PPG waveform analysis approach," in *2023 IEEE 4th International Multidisciplinary Conference on Engineering Technology (IMCET)*, Beirut, Lebanon, 2023, pp. 194–197. doi: 10.1109/IMCET59736.2023.10368236.

[15] JMSCR, "Blood typing and fingerprint analysis in medical research," *Journal of Medical Science and Clinical Research (JMSCR)*, vol. 4, no. 3, pp. 73–81, 2016. Available: http://jmscr.igmpublication.org/v4-i3/10%20jmscr.pdf.