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BLOOD GROUP DETECTION USING IMAGE PROCESSING AND FINGERPRINT

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ABSTRACT

Blood group identification plays a vital role in medical diagnosis, emergency healthcare, blood transfusion management, and forensic investigations. Conventional blood group determination methods require laboratory testing, specialized equipment, and trained personnel, which can be time-consuming and costly. Recent advancements in image processing and biometric technologies have opened new possibilities for non-invasive blood group prediction. This paper presents a blood group detection system using image processing and fingerprint analysis. The proposed framework utilizes fingerprint images as input and applies image preprocessing, feature extraction, and pattern analysis techniques to identify distinctive ridge characteristics associated with different blood groups. Image processing methods are employed to enhance fingerprint quality, remove noise, and extract relevant minutiae features such as ridge endings, bifurcations, and texture patterns. Machine learning algorithms are then used to classify fingerprints into corresponding blood group categories based on the extracted features. Experimental analysis demonstrates that the proposed approach provides an efficient, non-invasive, and automated solution for blood group prediction. The developed system has potential applications in healthcare management, biometric identification, and forensic science.

I. INTRODUCTION

In order to ensure that blood is compatible during medical operations including organ transplants, surgeries, and transfusions, blood group prediction is essential in both transfusion medicine and medical diagnostics. Based on the presence or lack of certain antigens on the surface of red blood cells, blood groups are categorised; the ABO and Rh blood group systems are the most widely used. Blood type identification is a critical process in both emergency and regular healthcare settings because it is necessary to avoid adverse responses.

Historically, laboratory-based methods for determining blood group have included physically collecting blood samples, mixing them with certain reagents (anti-sera), and then watching for reactions that reveal the blood type. Despite its effectiveness, this procedure is intrusive, time-consuming, and often calls for specialised tools and experienced staff.

Developments in deep learning and machine learning have created new avenues for automated and non-invasive blood type prediction techniques. These technologies make it possible to do image-based analysis, in which blood samples or other biometrics, such as fingerprints, are analysed using complex algorithms to precisely forecast blood groupings. These systems may examine patterns in blood pictures or other physiological indicators by using computer vision techniques and neural networks, providing a quicker, easier, and perhaps non-invasive substitute for conventional approaches.

Machine learning-based blood type prediction has enormous potential to increase diagnostic efficiency, decrease human error, and make blood typing more accessible in a variety of settings, including distant or resource-constrained places, as healthcare shifts towards automation and precision medicine. By incorporating these cutting-edge technology into clinical practice, blood group detection may be revolutionised, opening the door to more efficient and dependable medical treatment.

Deep Learning:

Computational models with many processing layers may learn representations of data with different degrees of abstraction thanks to deep learning. The state-of-the-art in a variety of fields, including drug discovery and genomics, has been significantly enhanced by these techniques, including voice recognition, visual object identification, and object detection. By employing the back propagation approach to tell a machine how to alter its internal parameters that are required to calculate the representation in each layer from the representation in the previous layer, deep learning finds complex structure in massive data sets. While recurrent networks have shed light on sequential data like text and voice, deep convolutional nets have made significant strides in processing pictures, video, speech, and audio.

Many facets of contemporary life are powered by machine-learning technology, including online searches, social network content filtering, e-commerce website suggestions, and the growing use of this technology in consumer goods like smartphones and cameras. Machine-learning algorithms are used to recognise things in photos, convert voice to text, match users' interests with news articles, posts, or goods, and choose relevant search results. These applications are increasingly using a class of methods known as deep learning. The capacity of traditional machine-learning methods to handle unprocessed natural data was constrained. For many years, building a machine learning or pattern recognition system required a great deal of domain knowledge and careful engineering to create a feature extractor that converted raw data (like an image's pixel values) into an appropriate internal representation or feature vector that the learning subsystem, usually a classifier, could use to identify or categorise patterns in the input. A collection of techniques known as representation learning enables a computer to automatically identify the representations required for detection or classification when it is given raw data. A representation at one level (beginning with the raw input) is transformed into a representation at a higher, somewhat more abstract level by each of the basic but non-linear modules that make up deep-learning methods, which are representation-learning techniques with several layers of representation. It is possible to learn very complicated functions by composing enough of these changes. Higher layers of representation for classification tasks minimise irrelevant variations and enhance elements of the input that are crucial for discriminating. The learnt features in the first layer of representation, for instance, usually indicate whether or not edges are present at certain orientations and positions in a picture, which is represented by an array of pixel values. Usually, the second layer finds motifs by identifying certain edge configurations, even if there are little differences in the edge placements. Subsequent layers would identify items as combinations of the motifs that the third layer assembled into bigger combinations that matched portions of recognised objects. Deep learning's main characteristic is that these feature layers are not created by human engineers; rather, they are acquired from data via a general-purpose learning process. Significant progress is being made by deep learning in addressing issues that have long eluded the artificial intelligence community's best efforts. It has shown to be very effective in identifying complex patterns in high-

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dimensional data, making it relevant to a wide range of fields in academia, industry, and government. It has outperformed other machine-learning techniques in predicting the activity of possible drug molecules, analysing particle accelerator data, reconstructing brain circuits, and predicting the effects of mutations in non-coding DNA on gene expression and disease, in addition to breaking records in image and speech recognition. Surprisingly, deep learning has shown very promising results for a variety of natural language comprehension tasks, including language translation, subject categorisation, sentiment analysis, and question answering. Because deep learning involves relatively little manual engineering and can readily leverage advances in the quantity of available computing and data, we believe it will have many more triumphs in the near future. This advancement will only be accelerated by new learning algorithms and deep neural network designs that are presently being developed.

Supervised learning

Supervised learning is the most popular kind of machine learning, whether it is deep or not. Let's imagine we want to develop a system that can identify if a picture shows a human, a vehicle, a home, or a pet. We start by gathering a large dataset of pictures of homes, vehicles, people, and animals, each of which is classified with its category. The machine generates an output in the form of a vector of scores, one for each category, after being presented a picture during training. Prior to training, it is rare that the targeted category would have the best score of all the categories. The error (or distance) between the produced scores and the intended score pattern is measured by an objective function that we construct. To lessen this inaccuracy, the machine then adjusts its internal customisable settings. These movable parameters, often referred to as weights, are actual numbers that operate as "knobs" to determine the machine's input-output function. Hundreds of millions of these movable weights and hundreds of millions of labelled samples to train the computer are possible in a typical deep learning system. The learning method produces a gradient vector for each weight that shows how much the error would grow or reduce if the weight were raised by a little amount in order to appropriately change the weight vector. In the opposite direction of the gradient vector, the weight vector is then modified. In the high-dimensional space of weight values, the goal function, averaged over all training samples, may be seen as a kind of hilly terrain. The direction of the landscape's steepest fall is indicated by the negative gradient vector, which brings it closer to a minimum where, on average, the output error is minimal. The majority of practitioners in practice use a process known as stochastic gradient descent (SGD). For a few instances, this entails displaying the input vector, calculating the outputs and errors, calculating the average gradient for those samples, and modifying the weights appropriately. Until the average of the objective function stops declining, the procedure is repeated for several small groups of samples from the training set. Because each tiny group of instances provides a noisy estimate of the average gradient over all examples, it is referred to be stochastic. When compared to far more complex optimisation approaches, this straightforward process often yields a decent set of weights remarkably rapidly. Following training, the system's performance is evaluated using a test set, which is an alternative collection of instances. This tests the machine's capacity for generalisation, or the ability to generate logical responses to novel inputs that it hasn't encountered during training.

On top of hand-engineered features, linear classifiers are used in many of the current practical applications of machine learning. The weighted sum of the feature vector components is calculated via a two-class linear classifier. The input is categorised as belonging to a certain category if the weighted total is greater than a certain threshold. We have known since the 1960s that linear classifiers are limited to dividing their input space into half-spaces that are separated by a hyperplane. The input-output function must, however, be extremely sensitive to specific minute variations (for instance, the difference between a white wolf and a breed of white dog called a Samoyed) and insensitive to irrelevant variations of the input, such as variations in the position, orientation, or illumination of an object, or variations in the pitch or accent of speech, in order to solve problems like image and speech recognition. While two photographs of a Samoyed and a wolf in the same posture and on comparable backdrops may be extremely similar, two images of two Samoyeds in various positions and situations may be highly different at the pixel level. The latter two could not be distinguished by a linear classifier or any other "shallow" classifier working with raw pixels, while the former two would be placed in the same category. Because of this, shallow classifiers need a good feature extractor that resolves the selectivity–invariance dilemma, which creates representations that are invariant to irrelevant aspects like the animal's pose but selective to the parts of the image that are crucial for discrimination. Generic non-linear features, like those found in the Gaussian kernel, may be used to increase the strength of classifiers, but they do not enable the learner to generalise very far from the training instances. The traditional approach is to manually create high-quality feature extractors, which calls for a significant level of subject knowledge and technical competence. However, if a general-purpose learning technique can be used to automatically learn excellent characteristics, then all of this may be avoided. This is deep learning's main benefit. A deep-learning architecture is a multilayer stack of basic modules, many of which calculate non-linear input-output mappings and all (or most) of which are sensitive to learning. To improve the representation's invariance and selectivity, each module in the stack modifies its input. A system can implement incredibly complex functions of its inputs with multiple non-linear layers, say with a depth of 5 to 20, that are both sensitive to small details, like differentiating Samoyeds from white wolves, and insensitive to large, irrelevant variations, like the background, pose, lighting, and surrounding objects.

II. LITERATURE SURVEY

1) A new framework for protecting medical data using Internet of Things sensors

The authors are P. Malathi, M. K. Kirubakaran, B. Khan, A. J., D. L. Rani, and K. Kasat.

The dissemination of medical records has been greatly aided by the Internet of Things (IoT), but it also presents security risks for patient-specific data required for remote hospital care. The transmission of data from various IoT sensors placed on a person's blood via networking devices to primary health care centres is not the focus of the bulk of publicly available security procedures for health information. We examined the possible dangers of unencrypted data transfer in this article, specifically with regard to network gateways and Internet of Things sensor systems. The research promotes remote health insurance data delivery to hospitals. The sensing element would be instantly encoded in the suggested health care information model before ever being transmitted to cryptographic procedures. The prototype solution was verified using a laboratory setup that used two-stage cryptography at the IoT sensor and two-stage decoding at the surgeon's operation receptor. Based on the transfer of medical data, the test findings for an IoT safety system seem to be satisfactory. The research creates new opportunities for IoT device information security.

2) CoviLearn: A Cyber-Physical Healthcare System with Machine Learning Integrated Smart X-Ray Device for Automatic Initial Screening of COVID-19 AUTHORS: D. Das, S. Ghosal, and S. P. Mohanty

Worldwide, the new coronavirus disease 2019 (COVID-19) pandemic is producing major health issues and having a significant effect on the international economy. For academics and medical professionals, evaluating the COVID-19 virus quickly and reliably has proven difficult. In order to enable healthcare professionals to conduct automated first screening of COVID-19 patients, we introduce a new machine learning (ML) integrated X-ray equipment in the Healthcare Cyber-Physical System (H-CPS) or smart healthcare framework (dubbed "CoviLearn"). For automated COVID-19 identification, we suggest convolutional neural network (CNN) models of X-ray pictures built within an X-ray apparatus. The suggested CoviLearn gadget will be helpful in determining if a person has COVID-19 or not based on their chest X-ray imaging. With the use of CoviLearn, clinicians will be able to quickly identify possible COVID-19 infections without requiring more invasive medical data samples, such blood or saliva. The endothelial tissues supporting the respiratory tract are attacked by COVID-19, and X-ray pictures may be utilised to assess a patient's lung condition. The suggested CoviLearn X-rays might be used to test for COVID-19 without the need for specialised test kits since all medical facilities have X-ray capabilities. Because X-ray equipment need a radiology specialist, our suggested automated analysis system CoviLearn, which has 98.98% accuracy, will be able to save medical personnel important time.

3) Pneumonia Disease Identification Using a Deep Learning and Machine Learning-Based Intelligent Computational Framework

The authors are R. Alturki, T. Vinh Hoang, W. M. Alenazy, M. D. Alshehri, and Y. Muhammad.

In order to assist a patient with pneumonia save their life and avoid further harm, it is important to detect the deadly and widespread illness in its early stages. Chest X-rays, CT scans, blood and sputum cultures, fluid samples, bronchoscopies, and pulse oximetry are among the methods used to diagnose pneumonia. Medical image analysis is regarded as one of the most promising research topics and is essential in the identification of several illnesses, including pneumonia, COVID-19, MERS, and others. An professional radiologist with knowledge and experience in the chosen field is required to effectively analyse chest X-ray pictures. About two thirds of people worldwide still lack access to radiologists for illness diagnosis, according to a World Health Organisation (WHO) research. In order to detect pneumonia illness effectively and efficiently, this research suggests a DL framework. To extract relevant features from the chest X-ray pictures, a variety of Deep Convolutional Neural Network (DCNN) transfer learning approaches are used, including AlexNet, SqueezeNet, VGG16, VGG19, and Inception-V3. Several machine learning (ML) classifiers are used in this investigation. The dataset of chest CT and X-ray images has been used to train and evaluate the suggested system. Various performance metrics have been used to assess the stability and efficacy of the suggested system. The goal of the suggested approach is to assist and benefit medical professionals in correctly and quickly diagnosing pneumonia.

4) Using human genetic data for machine learning techniques to identify and classify COVID-19

M. T. Ahemad, M. A. Hameed, and R. Vankdothu are the authors.

One illness linked to coronavirus is coronavirus. COVID-19 has been deemed a pandemic by the World Health Organisation. 212 countries and territories throughout the globe are affected. It is still required to examine and spot patterns in lung X-ray images. A person's exposure to viruses may be reduced or avoided with early identification. Manual diagnosis takes a lot of time and effort. Its discovery is quite alarming since the COVID-19 virus may infect people anywhere in the globe. This work aims to discover and categorise coronaviruses using machine learning. It is expected that COVID-19 would be classified and differentiated in computer-aided diagnosis (CAD) and CT-lung screening. Clinical samples from patients with corona infections were used in combination with a number of machine learning techniques, such as Decision Tree, Support Vector Machine, K-means clustering, and Radial Basis Function. Some medical experts believe that a lung CT scan is more accurate and less costly than an RT-PCR test, which they believe is the most cost-effective and dependable method of identifying Covid-19 patients. Clinical specimens include things like whole blood samples, serum samples, and respiratory secretions. These tissues are utilised to evaluate 15 distinct parameters as a consequence of the previous clinical examinations. The pre-processing stage that follows the CT lung screening collection is part of the proposed four-phase CAD system. This step improves the appearance of ground-glass opacities (GGOs) nodules, which are initially very fuzzy and poorly contrasting since there is no contrast. A modified K-means method will be used to identify and divide these zones. To classify the polluted zones discovered during the detection phase, machine learning classifiers with a 50x50 pixel resolution will employ radial basis functions (RBF) and support vector machines (SVM) as the input and target data. A graphical user interface (GUI) tool designed to assist physicians in receiving precise results may be used to enter the 15 input pieces collected from clinical specimens.

Authors: S. Akter, M. Amina, and N. Mansoor

5) Early Diagnosis and Comparative Evaluation of Various Machine Learning Algorithms for Myocardial Infarction Prediction

Myocardial infarction, another name for a heart attack, is one of the main causes of morbidity worldwide. As a result, the identification and prognosis of cardiac disease is encouraging several researchers to create sophisticated medical decision support systems. Given the vast volume of clinical data provided by healthcare, machine learning has been shown to be effective in assisting with prediction and decision-making. The goal of this research is to increase the precision of machine learning models that can aid in heart attack prediction and decision-making. Support Vector Machine, Random Forest, K Nearest Neighbours, Gaussian Naive Bayes, Decision Tree, and Logistic Regression are the six machine learning classification techniques that we have used. Furthermore, a thorough comparison of machine learning methods has been conducted. According to our study, machine learning approaches combined with data balancing strategies are useful tools for predicting strokes in cases when the data is unbalanced. As a result, our model uses the Synthetic Minority Over-Sampling Technique (SMOTE). According to performance measures, Random Forest is thus expected to perform best in heart attack prediction, with the maximum accuracy of 96%.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM:

- ❖ Blood group identification in the current system was mostly carried out using

MATLAB simulations, concentrating only on blood pictures. Accurate blood type categorisation and detection were achieved by combining deep learning techniques with image processing techniques. In order to produce photos that closely matched specified images in the system's dataset, raw blood images had to be gathered and processed in MATLAB. The diverse components found in blood samples may be effectively classified and differentiated thanks to our picture matching technique.

- Blood samples were taken in a clear glass container and combined with anti-serum to perform the detection. After that, digital pictures of the blood and anti-serum interaction were taken and processed pixel by pixel. Automated blood type identification was made possible by further refining these pictures using image processing techniques. Accurate categorisation via simulation was made possible by the deep learning algorithms used in MATLAB, which sped up the study. In order to ensure that the processed pictures matched those in the established dataset, a significant quantity of data was processed utilising hidden layers with activation functions.
- The final result included comparing the processed blood pictures with a stored dataset, and the system depended on conducting several rounds to maximise accuracy. By automating blood group identification using image analysis on the MATLAB platform, this technique demonstrated efficiency in replicating the classification process while saving time. A thorough and accurate examination of blood samples was made possible by the use of deep learning methods and image processing.

DISADVANTAGES OF EXISTING SYSTEM:

- Although the current method for detecting blood groups from blood pictures using MATLAB simulations has proven successful, it has a number of drawbacks that restrict its scalability and practical use.
- The system's detecting capabilities are limited to using just blood pictures. This necessitates the time-consuming and sometimes intrusive physical collection of blood samples. Furthermore, the technology is less appropriate for rapid or non-invasive testing situations due to the need for laboratory conditions to prepare and acquire blood pictures.
- Hardware and Resource Dependency: MATLAB is a resource-intensive program that needs a lot of computing power to execute simulations, particularly when deep learning training or processing huge datasets. In healthcare facilities with limited resources or those that are mobile, this reliance on high-performance technology may not be practical.
- human Preparation and Image Capturing: The human intervention required to mix blood with anti-serum and take pictures might lead to inconsistent findings since sample preparation and image quality can vary. The technique is made more difficult and less efficient by the need for regulated conditions in order to produce correct photographs.
- Processing Speed and Iterative Nature: To get the best classification results, MATLAB-based simulations—especially those that depend on deep

learning and image processing techniques—need to go through many iterations. The system's real-time application capabilities may be limited by this iterative process's slowness, particularly when working with intricate models and huge datasets.

PROPOSED SYSTEM:

- ❖ By combining deep learning models for both fingerprint and blood image-based detection, the suggested system offers a more flexible and contemporary method of blood type identification. With Flask as the web framework, HTML, CSS, and JavaScript for the frontend interface, and Python for backend development, this system guarantees a smooth user experience via a web-based platform. There are two different modes of operation for the suggested system.
- ❖ Blood Group Detection Using Blood photos: This mode use the MobileNetV2 architecture, a more effective and portable deep learning model, to identify blood groups using blood photos, much as the previous system. 500 of the 750 blood pictures in the dataset were utilised for training, while the remaining 250 were used for testing. By using deep learning algorithms to evaluate these photos, the model automatically classifies the blood type based on visual information taken from the samples.
- ❖ Blood Group Detection Using Fingerprint photographs: The suggested system's unique feature is its non-invasive blood group detection using fingerprint photographs. The MobileNetV2 architecture is also used in this mode, which is trained on a bigger dataset of 10,477 fingerprint images—6,000 of which are used for training and 4,477 for testing. The model provides a non-invasive substitute for conventional techniques by predicting blood types by examining fingerprint patterns without the need for a blood sample.
- ❖ Both modes use convolutional neural networks to find important patterns in the input photos, using the ability of deep learning for image categorisation. By using MobileNetV2, the system can handle a broad range of data inputs while maintaining computational efficiency. The system offers a versatile solution that can be implemented in clinical settings or accessible remotely over the internet, and it is made to integrate with healthcare applications.
- ❖ To automatically identify blood types, the suggested method analyses fingerprint and blood image data. To guarantee correctness, the models are trained and verified on sizable datasets. This method makes the system flexible enough to accommodate many use cases by allowing it to manage the real-world variability in blood samples and fingerprints.

ADVANTAGES OF PROPOSED SYSTEM:

- ❖ In addition to addressing the shortcomings of the previous system, the suggested blood group recognition method adds novel features for enhanced functionality and user experience.
- ❖ Non-Invasive Detection: The inclusion of fingerprint-based blood group detection is one of the suggested system's biggest benefits. By doing away with the need for actual blood samples, this non-invasive technique makes life easier and less unpleasant for people, particularly when blood collection is difficult or uncomfortable.

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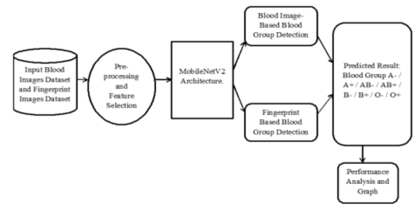
- ❖ High Accuracy and Efficiency: High accuracy is ensured in fingerprint and blood image identification by using the MobileNetV2 architecture. The system maintains a good training accuracy of 94% and validation accuracy of 90% for fingerprint pictures, while achieving a flawless training and validation accuracy of 100% for blood photos. These results show how accurate and dependable the system is in classifying blood types in both modes.
- ❖ Real-Time and Automated identification: By automating the whole blood group identification process, the suggested system drastically cuts down on the amount of time needed for manual picture capture, analysis, and blood sample preparation. Users may get findings instantly thanks to the deep learning models included into the online platform, which makes the system appropriate for both regular medical exams and emergency scenarios.
- ❖ Scalability and accessibility: The suggested system is web-based and was developed using Flask and Python, making it simple to deploy on a variety of platforms, including computers and mobile phones. Because of its online accessibility, it may be used in a variety of settings where quick and precise blood group identification is crucial, including clinics, hospitals, and distant healthcare facilities.
- ❖ Resource Efficiency: Real-time applications benefit greatly from the MobileNetV2 architecture's reputation for being lightweight and resource-efficient. This system may operate well on common hardware, allowing for quicker processing and wider deployment without requiring expensive computing sets, in contrast to the prior approach, which depended on MATLAB and needed significant computational resources.

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules Description

Data Collection:

- ❖ We create the data gathering procedure in the first module of the blood group detection utilising blood samples. The process of gathering data is the first actual step in creating a deep learning model. This is a crucial stage that will influence the model's performance; the more and better data we collect, the better the model will function.
- ❖ Data may be gathered using a variety of methods, including human interventions and web scraping. The model folder contains the dataset. The dataset is sourced from Kaggle, a well-known dataset resource. The dataset's URL is as follows:
- ❖ https://www.kaggle.com/datasets/jayaprakashpondy/blood-dataset is the link to the Kaggle dataset.

Dataset:

- ❖ Make directories for A-, A+, AB-, AB+, B-, B+, O-, and O+ blood types.
- ❖ Go Put each picture in the directory that matches its blood type. For instance:
- ❖ Sort pictures for each of the other blood types (A+, AB-, AB+, B-, B+, O-). If an image is labelled as A-, transfer it to the

A-directory. If it is labelled as O+, move it to the O+directory.

- It is simple to import the dataset into your deep learning system when it is arranged in this way. In order to ensure that the right photos are loaded for each class and that the overall dataset size is 750, it is easy to provide the directory path for each class when loading the data.

Data Preparation:

- To make sure the data is appropriate for training, preprocessing is essential throughout the data preparation phase. This includes actions like standardising pixel values, scaling photos to a standard size, and, if required, encoding labels. The ImageDataGenerator from Keras may be used to do this. For example, the Target_size argument may be set to (img_height, img_width) = (240, 240) to resize pictures to a standard size of 240x240 pixels.
- Additionally, by setting the rescale option to 1./255, pixel values may be normalised. Additionally, the training data may be improved by using data augmentation methods like zoom and random shear. These methods may be used to efficiently preprocess the data and enhance the deep learning model's performance.

Feature Extraction:

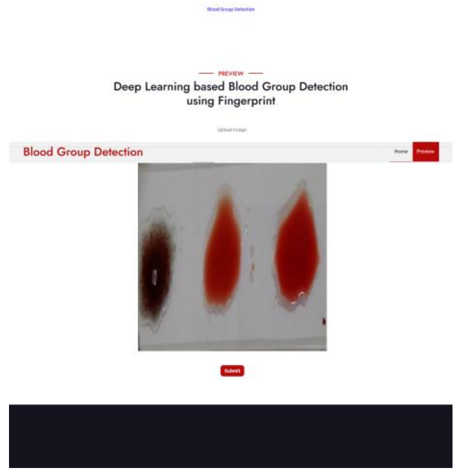
- Exact feature extraction may not necessarily be required for models such as MobileNetV2, which are pre-trained with feature extraction layers. These pre-trained layers may keep their learnt representations while avoiding further updates during training by having trainable = False set.
- Setting trainable = False in the context of MobileNetV2 guarantees that the feature extraction layers' weights stay constant during training. This method is often used in transfer learning situations, when a pre-trained model is refined for a particular job, such object identification or image classification, using a fresh dataset.
- By using this approach, we achieve a balance between using potent pre-trained representations and customising the model for our particular dataset, which eventually enhances training effectiveness and model performance.

Splitting the dataset:

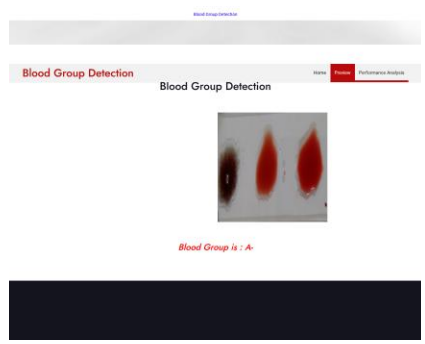
- The picture dataset will be separated into training and testing sets in this module. Divide the dataset into two parts: test and train. 20% is test data and 80% is train data. By doing this, the model will be trained on a portion of the data, its performance will be verified, and its correctness will be assessed by testing it on unknown data. Divide the dataset into test and train sets. 20% is test data and 80% is train data.
- To assess how well your model is doing, separate your dataset into training and validation sets. Generally, an 80-20 split may be used, however this might change depending on the size of your dataset and your particular needs.

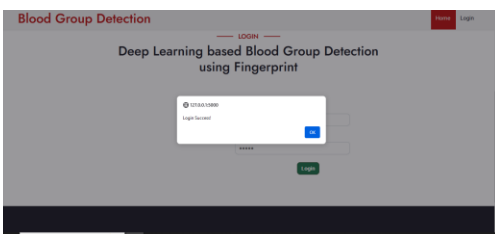
V. SCREEN SHOTS


Blood Group Detection
Home
Login
LOGIN
Deep Learning based Blood Group Detection
using Fingerprint
Login

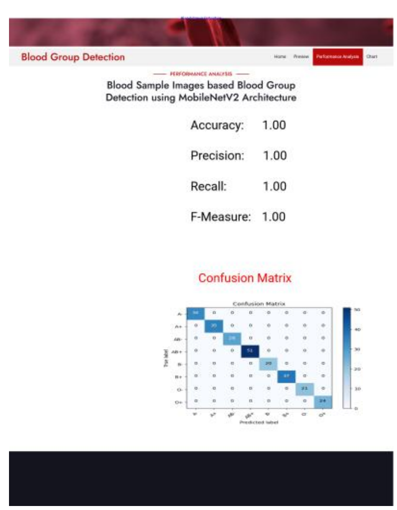

PREVIEW
Deep Learning based Blood Group Detection
using Fingerprint
Blood Group Detection
Home
Preview
Submit


Blood Group Detection
Home
Login
LOGIN
Deep Learning based Blood Group Detection
using Fingerprint
Login


Blood Group Detection
Home
Preview
Performance Analysis
Blood Group Detection
Blood Group is : A-


Blood Group Detection
Home
Login
LOGIN
Deep Learning based Blood Group Detection
using Fingerprint
OK
Login


Blood Group Detection
Home
Preview
PREVIEW
Deep Learning based Blood Group Detection
using Fingerprint
Submit


Blood Group Detection
PERFORMANCE ANALYSIS
Blood Sample Images based Blood Group
Detection using MobileNetV2 Architecture
Accuracy: 1.00
Precision: 1.00
Recall: 1.00
F-Measure: 1.00
Confusion Matrix

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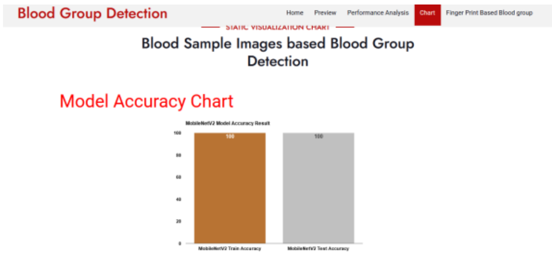

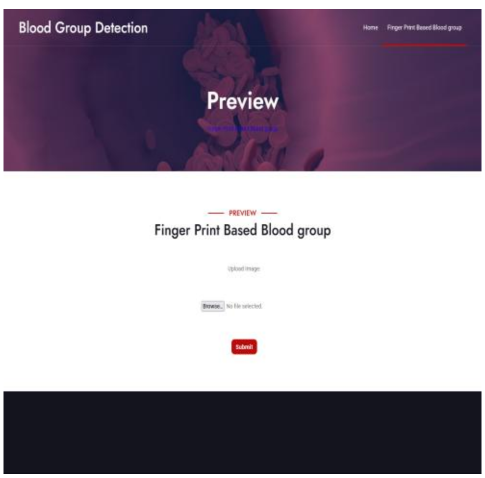

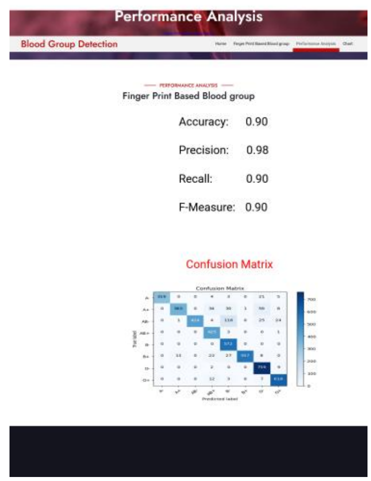

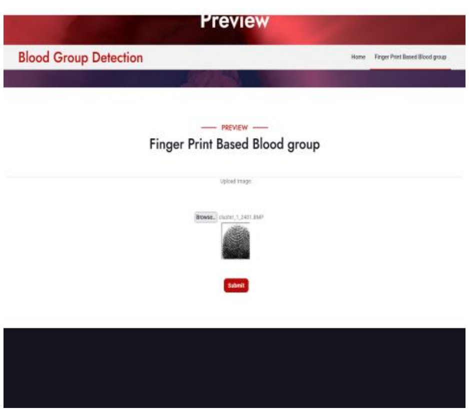

VI. CONCLUSION

This study presented a blood group detection framework based on image processing and fingerprint analysis techniques. The proposed system utilizes fingerprint images to extract unique ridge patterns and biometric features that are subsequently analyzed using machine learning algorithms for blood group classification. Image processing methods effectively enhance fingerprint quality and improve feature extraction accuracy, while intelligent classification models enable automated prediction of blood group categories. Experimental observations indicate that the proposed approach provides a fast, cost-effective, and non-invasive alternative to conventional laboratory-based blood group determination methods. Furthermore, the integration of image processing and machine learning enhances prediction efficiency and supports automated biometric analysis. The proposed framework demonstrates potential for applications in healthcare systems, forensic investigations, and biometric authentication environments. Future research may focus on incorporating deep learning architectures, multimodal biometric features, larger datasets, and real-time implementation techniques to further improve blood group prediction accuracy and system reliability.

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