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Automated Axial Triradius Detection and Classification using Deep Learning: A Preliminary Study for Non-Invasive Cardiac Screening

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***Abstract*— The study of epidermal ridges on fingers and palm has long been examined in connection with genetic characteristics and other medical disorders, such as congenital heart disease. The axial triradius is one of the features of the dermatoglyphics that has gained a lot of interest because of its use as a non-invasive means of assessing health in the early years. In the traditional approach to dermatoglyphic analysis, the process involves manual examination and interpretation, which can be labor-intensive and challenging in large-scale screening scenarios, especially in resource-limited environments. In the present work an automated framework based on palm-print image and deep-learning techniques for axial triradius analysis is explored. Regions of the palms were detected by MediaPipe and the axial triradius was localized by a custom-trained object detection model of YOLOv5. A Convolutional Neural Network (CNN) using the VGG16 architecture was then used for pattern classification between normal and disease palm. The entire framework was wrapped into a web-based application made with flask and mysql for easier deployment. To develop the model and evaluate, 500 palm-print images were used. The YOLOv5 model demonstrated high detection accuracy of 90% or above for the localization of the target anatomical landmark (axial triradius) in the palm-print image for different palm-print samples. The overall accuracy of classification experiments using the VGG16 network was 65%, and its precision was between 0.64 and 0.66, its recall was 0.65, and its F1-scores ranged from 0.64 to 0.65. The results validate the feasibility of the proposed automatic localization of landmarks and deep-learning–based analysis for dermatoglyphic screening applications. The proposed framework provides a basis for the automatic analysis of palm prints using general public image and computing tools. Future enhancements will involve increasing dataset diversity, adding additional dermatoglyphic parameters, and using more sophisticated learning architectures to achieve better classification accuracy and to enable future clinical validation studies.**

***Index Terms*— Dermatoglyphics, Axial Triradius, Palm Print Analysis, Congenital Heart Disease Screening, Deep Learning, Object Detection, YOLOv5, Convolutional Neural Network (CNN), VGG16, Medical Image Analysis, Non-Invasive Diagnostics, Computer-Aided Screening.**

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I. INTRODUCTION

Dermatoglyphics are "the patterns in the epidermal ridges found on the fingers and palms. They are established during early fetal development (around sixth to the 13th week of gestation) and are permanently fixed [3, 4]. They are believed to be formed under the influence of genetic and in utero environmental factors and therefore exhibit unique ridge characteristics which have been extensively studied in inherited disorders and disease susceptibility [5]. The presence of several dermatoglyphic features has been the subject of considerable interest as it has been reported to have a relationship with congenital heart diseases (CHD), Down syndrome, diabetes mellitus [1]–[5] amongst others and has been the focus of these studies. Traditional dermatoglyphics are based on taking palm prints with the use of ink, then manually measuring and examining them by trained dermatoglyphics experts. These techniques have played a significant role in the dermatoglyphic studies but they are also tedious and time consuming and are observer dependent [3, 4]. This limitation hinders their usability in large-scale screening and in clinical practice. With the ubiquitous digital imaging devices and recent developments of Artificial Intelligence (AI), Computer Vision, and Deep Learning, automated dermatoglyphic analysis becomes possible [18, 28]. These automated systems offer quicker and more objective assessment of palm-print qualities and enable effective palm-print screening in a setting where advanced diagnostic resources are scarce. Diagnosis of any congenital heart disease at an early age is significant as early diagnosis and timely treatment play an important role in clinical outcome and prognosis of congenital heart disease [29]. Automated analysis of palm-print images captured using easily available imaging equipment is a viable solution to conduct initial health assessment and facilitate other screening efforts in the hard-to-reach populations.

In the present work, an automated framework for the axial triradius analysis is explored based on digital palm-print images. Palm regions are extracted by MediaPipe framework [21] and localization of axial triradius is done by a customized YOLOv5 object detection model [9] [13]. The features extracted from the palm-print are then fed to a VGG16 based Convolutional Neural Network (CNN) for further classification [6] [15] into normal and disease associated palm-print. The entire workflow is implemented in a web-based platform for submitting images, processing and visualization of results. The main findings of the study are briefly summarized as follows; i. Automated end-to-end system for axial triradius analysis using computer vision and deep-learning [6], [9]. ii. YOLOv5 model training to accurately locate the axial triradius in various palm-print images [13]. iii. Evaluation of a VGG16 based CNN for classification of palm-print patterns with normal and disease conditions [15]. iv. Incorporation of the analytical pipeline into a web-based analytical platform for efficient image processing and results generation. v. In-depth performance evaluation and discussion of existing challenges and the future directions for research.

II. LITERATURE SURVEY

The study of dermatoglyphics has long been involved in the research of human developmental biology and susceptibility to disease. Initial studies were mainly directed towards finding associations between the properties of ridge pattern and the incidence of certain congenital and systemic diseases [1]–[5]. With the advent of image processing, machine learning, and deep learning, this field has been expanded to automated analysis of palm-prints and fingerprints. In the subsequent sections, key advances in the fields of dermatoglyphic assessment, automatic palm-print analysis, and AI in medical imaging are highlighted.

A. Birthmarks and Health Issues

There have been a number of reports of dermatoglyphic characteristics being associated with a number of congenital and systemic disorders. Several conditions such as Down syndrome, diabetes mellitus and congenital heart diseases have been associated with the variations in fingerprint configuration, in the number of ridges, in the position of the axial triradius and in the angle of the ATD [1], [3], [4] and [5] respectively. Some studies found that persons with CHD had an increased ATD angle and a distally displaced axial triradius when compared to healthy controls [1], [5]. The fundamental research revealed that there are substantial variations among palmar ridge configuration and between the triradial patterns, thus providing an early foundation for dermatoglyphic markers to be used in medical research [3, 4]. Recent studies have focused on the dermatoglyphic differences between particular cardiac anomalies and automated estimation methods to confirm that dermatoglyphics could be used as a non-invasive supplementary screening tool [20].

B. Automated Dermatoglyphic and Palm-Print Analysis

Over the years, advancements in computer vision and machine learning gradually shifted the dermatoglyphic analysis from manual observation to automated feature extraction. Early work mostly related to biometric identification and authentication systems [11] and further work was directed toward healthcare and diagnostic applications [24]. The enhancement techniques used to improve the palm-print image, the optimization of image quality, the extraction of minutiae features as well as that of the triradius were previously investigated [7, 11, 24, 26]. Recent years have seen these advances speed up with the introduction of deep-learning techniques, including Convolutional Neural Networks (CNNs) and Object-Detection (OD) networks like YOLO and Faster R-CNN, which have proven to be effective in image classification and localization. These capabilities make this an appropriate base for automatic analysis of dermatoglyphic features [9,13].

C. Convolutional Deep Learning for Medical Imaging

Deep learning is an important technology that has gained widespread interest in medical images' analysis and diagnostic decision support. CNN has shown good results in various tasks, such as diabetic retinopathy detection, skin lesion classification, radiological image interpretation and pathological image analysis, among others [17]. Recent surveys and review articles have pointed to the growing importance of deep learning in a variety of healthcare fields such as radiology [17], ophthalmology [18], pathology [28] and clinical diagnostics [29]. This has been driven by powerful architectures like AlexNet [6], VGGNet [15], GoogLeNet/Inception [16] and ResNet [7] and real-time object-detection systems like YOLO [13] are advancing localization and detection in medical imaging.

D. Research Gap

Although great efforts have been made in dermatoglyphic studies and automatic palm-print analysis, there are still some problems to be solved. Numerous studies have been reported that still rely on manual or semi-automated measurement procedures, which involve long analysis times and different interpretation of the results [9, 13]. The current automatic palm print systems focus on biometric recognition instead of medical screening and many focus on each of the individual stages in the system rather than an overall analysis approach [6, 15]. The localization of the axial triradius is a very difficult task due to the slight anatomical features and the sensitivity of the image quality. Moreover, there are restrictive availability of clinically validated datasets limiting the thorough assessment of automated dermatoglyphic screening systems. Solving these problems demands integrated solutions that integrate reliable feature localization, automatic classification and practical deployment into a single workflow.

III. METHODOLOGY

The automated dermatoglyphic analysis framework was designed as a multi-stage pipeline comprising of acquiring palm images, preprocessing, locating the axial triradius, extracting features, classification through deep learning and presentation. The entire procedure is shown in Fig. 1. The system uses computer vision algorithms and deep-learning models to automatically process palm-print images and assist with initial screening of dermatoglyphic patterns related to cardiac diseases.

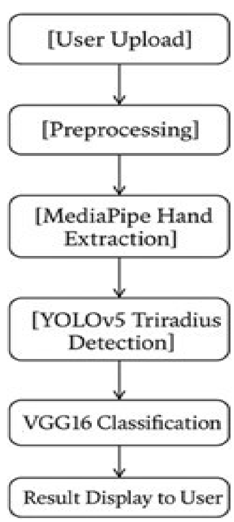

Fig. 1. Proposed methodology for automated axial triradius analysis and palm-print classification

A. System Overview

The overall framework involves the following five stages: User interaction and data management, Image pre-processing, Localization of the axial triradius, Feature extraction, Deep learning classification and Result presentation. Every stage has a particular role in the analysis pipeline and it is used for the automatic evaluation of palm-print images. The major steps of the proposed methodology are briefly outlined in Table I.

TABLE I. MAJOR STAGES OF THE PROPOSED METHODOLOGY

Phase	Description
User Interaction and Data Management	Collection, storage, and management of palm-print images through a web-based interface
Image Preprocessing	Enhancement of image quality through grayscale conversion and noise reduction
Axial Triradius Localization	Detection of the axial triradius using the YOLOv5 object detection model
Feature Extraction	Computation of dermatoglyphic measurements including the ATD angle
Classification and Result Presentation	Classification using VGG16 and display of prediction results through the web interface

B. Phase 1: User Interaction and Data Management

The first phase of the framework involves the acquisition of images and the organization of the data using a web application in the Flask framework that is connected to a MySQL database. The first phase of the framework is responsible for the acquisition of images and the organization of the data, using a web application in the Flask framework that is coupled with a MySQL database. The platform is secured by users with security authentication prior to uploading palm-print images to be analyzed. The system can handle JPEG and PNG images obtained from either a smartphone camera or a conventional digital imaging system, allowing for easy image acquisition and storage. For the development and evaluation of the model, 500 images of palm prints were used. The dataset consisted of two classes, among them being Normal and Diseased classes. In Fig. 2 some typical examples are shown from each class. In order to enhance the robustness of the model and alleviate the problem of overfitting, multiple data enhancement methods were implemented during model training, which included rotation, horizontal flip, brightness adjustment, contrast enhancement, cropping and scaling operations.

Fig. 2. Representative palm-print images belonging to Normal and Diseased classes

C. Phase 2: Image Preprocessing

Before extracting features, we pre-processed the images to enhance the visibility of dermatoglyphic structures and to minimize unwanted variations in the images. The uploaded RGB palm-print image was first converted to grayscale using OpenCV cvtColor() function to reduce computational complexity and preserve ridge-pattern information. Then a Gaussian filtering was applied with kernel size of 5 × 5 and standard deviation 1.0 to suppress high frequency noise while preserving structural features of dermatoglyphic ridges. Fig. 3 shows examples of the preprocessing steps. This leads to improved contrast and visibility of features in the resulting images, which in turn allows for more reliable localization of anatomical landmarks for subsequent analysis.

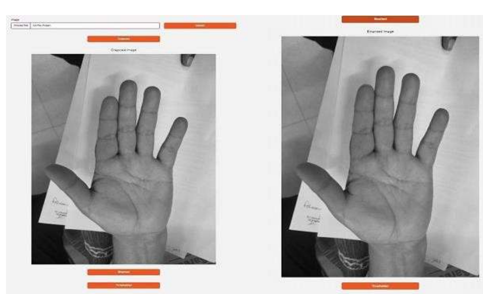

Fig. 3. Preprocessing stages showing grayscale conversion and noise-reduced palm-print images

The palm region was extracted using the MediaPipe Hands framework after preprocessing. MediaPipe detects twenty-one anatomical hand landmarks and separates the palm area from the background. The extracted landmark coordinates are anatomical reference points for later use in triradius localization and ATD-angle estimation. The framework is able to process in real time and has high performance under different hand orientations and illumination conditions [21–23].

D. Phase 3: Axial Triradius Localization and Feature Extraction

A proper determination of the axial triradius is a necessary step in the dermatoglyphic analysis. This anatomical landmark was detected using a custom trained YOLOv5 object detection model. YOLOv5 was chosen because of its better localization of objects, computational efficiency and capacity to perform tasks of real-time image analysis [2], [9], [13].

The model was trained with the YOLOv5s architecture, at an input resolution of 640 × 640 pixels, for 100 training epochs and a batch size of 16. We used Stochastic Gradient Descent with momentum for optimization. The initial learning rate was set to 0.01 and we used cosine annealing scheduling for adjusting the learning rate. After the axial triradius was detected, the geometric dermatoglyphic measurements were extracted using the detected triradius location and the MediaPipe generated landmark coordinates. Special attention was given to the estimation of the ATD angle which is formed by the triradius below the index finger (a), the axial triradius (t) and the triradius below the little finger (d). The measurement procedure is shown in Fig. 4.

Fig. 4. ATD-angle estimation using detected dermatoglyphic landmarks

E. Phase 4: Deep Learning Classification

The processed palm-print images were then analyzed using a Convolutional Neural Network based on the VGG16 architecture. The purpose of this stage was to classify palm-print images into Normal and Diseased classes based on dermatoglyphic features.

The network was initialized with ImageNet pre-trained weights for transfer learning and the higher-level convolutional and fully connected layers were fine-tuned with the palm-print dataset. The network was trained with the adam optimizer with a learning rate of 0.0001 and binary cross entropy loss. The training was performed with a batch size of 32 and 50 epochs. The dataset was divided into training, validation and testing subsets with ratio 70%, 15% and 15% respectively. To reduce overfitting and improve model generalization, dropout regularization and early stopping were used. The principal training parameters used for the VGG16 classification model are summarized in Table II.

TABLE II. VGG16 TRAINING CONFIGURATION

Parameter	Value
Input Image Size	224 × 224 × 3
Architecture	VGG16
Optimizer	Adam
Learning Rate	0.0001
Loss Function	Binary Cross-Entropy
Batch Size	32
Epochs	50
Training Split	70%
Validation Split	15%
Testing Split	15%
Dropout Rate	0.5
Early Stopping Patience	10 Epochs

F. Phase 5: Result Presentation

The last stage of the framework presents the classification result on the web-based interface. The displayed information includes predicted class label, confidence score of classification, estimated ATD angle and YOLOv5 detection confidence related to axial triradius localization. The output interface offers interpretable summary of the analysis and enables users to visualize the prediction results with the detected dermatoglyphic features. The interface of the presentation of the result is demonstrated in Fig. 5.

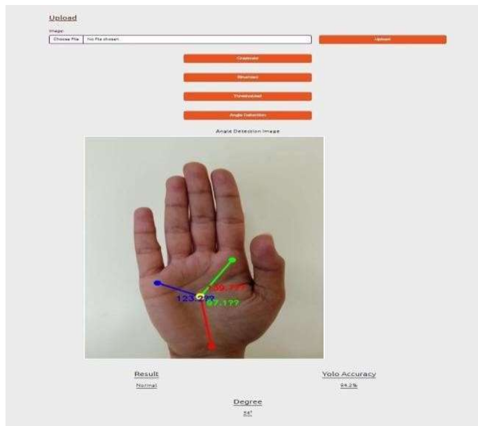

Fig. 5. Result presentation interface displaying classification results, ATD-angle estimation, and triradius localization confidence

G. Research Contribution

The developed framework integrates palm region extraction, automatic axial triradius localization, dermatoglyphic feature computation and deep learning based classification into a single analysis pipeline. The combination of MediaPipe, YOLOv5 and VGG16 enables to automate the assessment of palm print images without the need of dermatoglyphic measurements manually . The feasibility of integrating computer vision and deep-learning techniques for automated dermatoglyphic analysis and preliminary cardiac-health screening applications is demonstrated by experimental evaluation.

IV. Experimental Setup and Implementation

This section describes the dataset properties, implementation environment, software tools, training procedures, and evaluation metrics used to develop and evaluate the proposed dermatoglyphic analysis framework.

A. Dataset

In this study, a self-prepared 500 palm print images was created as a custom dataset. The dataset had two classes, Normal (Class 0) and Diseased (Class 1) corresponding to people with no cardiac related disease and the people with cardiac related disease, respectively. The images of palm prints were captured by a smartphone camera under controlled conditions and saved as JPEG and PNG images. The images were cropped to 224 x 224 pixels for VGG16 classification and 640 x 640 pixels for axial triradius localization using YOLOv5 [6], [9], [13], [20] for compatibility with the deep learning model.

The distribution of class was almost balanced with around 48.8% Normal and 51.2% Diseased samples. To enhance YOLOv5 training and evaluation, the triradius locations were annotated manually along the axial views. The dataset has been split in a stratified manner with 70% images used for training, 15% for validation, and 15% for testing. The data was also augmented with techniques such as rotation, horizontal flipping, brightness adjustment, contrast enhancement, zooming, and adding Gaussian noise [17, 18] to prevent overfitting and enhance model generalization. No names were given to the palm-print images collected before processing, and the handling of the data was done in accordance with the ethical norms of the institution for research using human participants [28], [29].

B. Implementation Tools and Technologies

The developed framework combines image preprocessing, localization of dermatoglyphic features, deep learning classification, database management, and web-based deployment within a single framework. The overall implementation architecture is drawn as shown in Fig. 6. The development was done mainly in Python (version

3.8+) programming language. The use of Flask (version 2.0) for the web application framework, MySQL (version 8.0) for data storage and user management. The image preprocessing operations were performed using OpenCV (version 4.5), while the numerical computations were performed using NumPy (version 1.21). The MediaPipe Hands framework (version 0.8.9) was used for hand landmark detection and palm-region extraction. YOLOv5 (version 6.0) implementation in PyTorch was used for axial triradius localization while TensorFlow/Keras (version 2.8) was used for the implementation and training of the VGG16 classification model.

Frontend development was done with HTML5, CSS3, JavaScript and Bootstrap 5.0, which makes the interface responsive and can be used on different devices. The development and testing activities were mainly done in Visual Studio Code with a local XAMPP server. As depicted in Fig. 6, the frontend interface communicates with the backend services, which, in turn, connect to the database layer and interact with the deep learning modules. Flask is used to handle the http requests, to coordinate communication between the trained models and the user interface, and MySQL is used for storing the prediction records and the user credentials. The palm-print images uploaded to the web interface are fed into MediaPipe, YOLOv5 and VGG16 one by one, and finally the user is returned with the final classification result.

The YOLOv5 model was trained with palm-print images with custom annotation and the model was tested on the axial triradius localization task with good performance in the localization task [2] [9] [13]. The VGG16 network was used for classification, which was initialized with the pre-trained weights from the ImageNet database and fine-tuned with palm-print images resized to 224 × 224 × 3 [6], [15], [20] for classification. The training used the Adam optimizer, binary cross-entropy loss function, dropout regularization and early stopping to enhance the generalization performance.

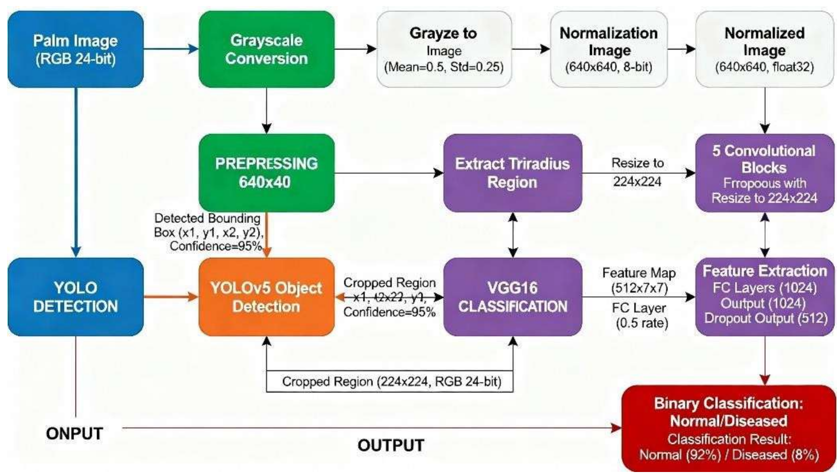

Fig. 6. System architecture of the implemented dermatoglyphic analysis framework

Standard machine-learning metrics such as accuracy, precision, recall, F1-score, specificity, Intersection over Union (IoU) and mean Average Precision (mAP) were used for model evaluation [17] [18]. Experiments were conducted in the following GPUs supported environments: NVIDIA GTX 1650 and Google Colab T4. Random seeds were fixed during experiments and hyperparameter settings were documented to ensure reproducibility and consistency of the results [18, 29].

V. Results and Discussion

In this section the functionality of developed system, the axial triradius localization results, classification performance and discussion about the results observed are presented.

A. System Functionality and User Interface

The web-based application was successfully integrated with a MySQL database using the Flask framework, and had no issues during the experimental evaluation. The functions of user registration, authentication and upload of palm-print image were performed consistently in different tests. Once the image was submitted, the automated processing pipeline performed the following: converting images to grayscale, removing noise, extracting palm region, localizing the axial triradius, and classifying the image without human intervention.

The UI was responsive on both desktop and mobile devices. The preprocessing, detection and classification modules were integrated, allowing the entire workflow from image acquisition to result generation to be seamlessly performed. A few screenshots of the developed application are shown in Fig. 5.

B. YOLOv5 Performance for Axial Triradius Localization

The performance of the modified YOLOv5 model was well suited for the localization of the axial triradius on the palm print data set. The average detection confidence was over 90%, the mean IoU was 0.82, precision was 0.91, and recall was 0.88, and the mAP@0.5 was 0.89. The results show that the axial triradius can be identified reliably and the prediction of the bounding-box is accurate in various palm-print samples.

No significant performance differences were found between manipulation of the hands and different skin tones. It was found that the localization accuracy was slightly degraded in the case of poor illumination and motion blur, but the performance in terms of detection remained unchanged. There were rare false positive detections mostly related to intersections of ridges in areas near the finger triradii.

C. VGG16 Classification Performance

VGG16-based Convolutional Neural Network was used to classify palm-print image into two classes namely Normal (Class 0) and Diseased (Class 1). The dataset partition was based on 70:15:15 train–validation–test strategy and classification performance was evaluated by this partition. The confusion matrix is shown in Fig. 8.

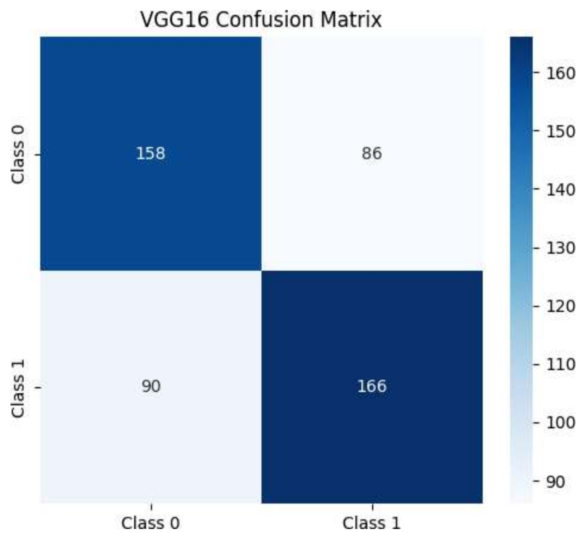

Fig. 8. Confusion matrix of the VGG16 classifier for Normal and Diseased palm-print classification

This confusion matrix depicts the number of true positive, true negative, false positive and false negative predictions made by the classifier. The overall classification accuracy of the model is around 65%, while the precision of the model is in the range 0.64-0.66, the model recall is around 0.65, and the F1-scores of the model are in the range 0.64-0.65. The results show that the network can well learn discriminative dermatoglyphic features relevant to the two classes, but the classification rate is still lower than the localization rate of the detector YOLOv5.

D. Interpretation of Results and Error Analysis

The overall classification accuracy of VGG16-based classifier on the tested dataset was 65%, which shows that VGG16-based classifier has the ability to differentiate the meaningful dermatoglyphic features between the Normal and Diseased classes. Despite moderate classification performance, the results have shown the palm-print features have some discriminative information useful for an automated screening application. The model gave good performance for both the Normal and Diseased classes as shown in table III, with precision rates of 0.64 and 0.66 respectively. The values of recall were the same for both classes (0.65) suggesting good performance in the identification of the samples belonging to each class. The F1-scores of 0.64 and 0.65 in turn show a balanced classification behaviour with no significant bias towards either class. Macro-average and weighted-average scores are close, indicating that the classifier was not heavily biased by the class imbalance, which is well balanced since there are only a few samples in each class.

TABLE III. VGG16 CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
Class 0 (Normal)	0.64	0.65	0.64	244
Class 1 (Diseased)	0.66	0.65	0.65	256
Accuracy	–	–	0.65	500
Macro Average	0.65	0.65	0.65	500
Weighted Average	0.65	0.65	0.65	500

It was found from the confusion matrix that about 35% of the samples were misclassified. Images of palms with less clear dermatoglyphic patterns, overlapping ridge patterns and lower image quality often had false predictions. The number of false negative predictions was noted when disease related dermatoglyphic characteristics were not very prominent and hence difficult to differentiate them from a normal one. These findings suggest that image quality, feature visibility and variation in the data sets have significant impacts on the classification performance. With the advancement of image acquisition protocols, increased image size, and more dermatoglyphic features being included in the data sets, classification errors and predictive accuracy should be reduced.

E. Comparison with Related Work

A comparative study with representative studies found in the literature is presented in Table IV. Previous research has been mainly on the manual or semi-automated dermatoglyphic evaluation, and some palm-print research has been performed for biometric authentication, but not for medical screening. A semi-automated triradius detection method was presented by Mahesha and Nagaraju for screening congenital heart disease, but it was difficult to compare with other methods because quantitative performance metrics were not reported. In their study, Zhang et al. confirmed palmprint identification accuracy over 98% with the task involved in biometric recognition instead of disease prediction. Medical screening differs from biometric authentication, in that small anatomical differences related to disease conditions must be identified, making the classification problem much more difficult.

The proposed framework consists of extracting palm images using MediaPipe, axial triradius localization using YOLOv5, and palm classification using VGG16, all in an end-to-end fashion. It is found that the classification accuracy achieved is 65%, which is lower than that of the recognition studies in biometrics but the result showed that dermatoglyphic analysis can be automated for preliminary screening of congenital heart diseases and it can be used as a basis for further clinical studies.

TABLE IV. COMPARISON WITH RELATED WORK

Study	Method	Application	Accuracy	Dataset Size
Mahesha and Nagaraju (2021)	Semi-automated triradius detection	CHD Screening	Not Reported	Limited
Zhang et al. (2003)	Online Palm-print Identification	Biometric Authentication	>98%	Large
Present Study	YOLOv5 + VGG16	CHD Screening	65%	500

F. Discussion

The results acquired here prove the possibility of using computer vision and deep learning methods for automated analysis of dermatoglyphics. The reliable localization performance of the YOLOv5 detector indicates that the triradius localization of palms can be robustly done across a wide variety of palm-print images with axial triradius identification. Even though the dermatoglyphic characteristics are subtle and complex, the VGG16 classifier showed moderate but balanced performance results, suggesting that disease-related information can be extracted from palm print images with the help of these characteristics.

The performance of classification was affected by several factors such as the size of the dataset, the variations in image quality, and the use of only one dermatoglyphic feature for classification. Lack of external validation data further reduces external validity of the current results. Therefore, it can be suggested that the proposed framework should be used as a preliminary screening and research-supportive system, and not as a standalone diagnostic system. Future studies will focus on expanding the dataset, adding more dermatoglyphic parameters, examining more sophisticated deep learning architectures, and large-scale clinical validation studies to enhance predictive power and clinical relevance.

VI. CONCLUSION AND FUTURE SCOPE

An automatic system for axial triradius–based palm-print analysis was designed and tested as a non-invasive method for initial cardiac health screening. The system proposed is based on the integration of a palm image preprocessing, a hand landmark detection using MediaPipe, an axial triradius localization based on YOLOv5, a classification based on VGG16 and a web-based deployment platform, all of them in a single system. Experimental results show that the YOLOv5 detector performed well in terms of localization accuracy with a detection precision rate of more than 90% and a mAP@0.5 value of 0.89. The final overall accuracy of VGG16 is 65% and it had balanced values of precision, recall and F1-score for both classes.

The acquired results validate that the dermatoglyphic features derived from palm-print images carry discriminative information which can be effectively used by deep learning models for automated palm-print classification. The high performance in terms of localization further confirms the suitability of axial triradius analysis as a measurable dermatoglyphic parameter for AI-enabled screening systems. While the performance of classification is still moderate, it sets a complete end-to-end framework for automated dermatoglyphic analysis and suggests a foundation for further research on a health assessment using palm print. The accuracy of the current classification is affected by factors such as the number of images included, images use a range of different qualities, features are limited and not as diverse as desired, and there is no external clinical validation. It should thus be viewed as a screening and research-support framework to be used as a first step, rather than as a diagnostic system in itself. The diagnosis and treatment of patients must be continued using a sound medical assessment protocol and specialist evaluation.

Future studies should build on larger and more comprehensive data sets obtained under different imaging conditions and clinically-tested ground-truth annotations. The integration of other dermatoglyphic parameters, the use of advanced deep learning architectures, the multimodal feature fusion, and large-scale clinical validation studies are expected to enhance classification performance and boost the generalizability of the model. The research and clinical efforts of the participants along with the collaboration of researchers, clinicians, and healthcare institutions will continue to help develop accurate AI-enabled dermatoglyphic screening systems. Proposed system here will serve as a practical basis for developing screening platform for future smart phones that can offer a convenient and affordable preliminary cardiac risk assessment, and can be used in conjunction with clinical practice.

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