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PalmPrint: A System of Deep Learning Approaches for Dermatoglyphics and Cognitive Personality Insights

Mohit Lohar[1], Pavan Temghare[2], Dipali Patil[3], Prashant Walke[4], Sandesh Pawar[5] and Pratik Kokate[6]
[1-6]Department of Information Technology JSPM's RSCOE, Pune
Email: lmohit272@gmail.com, pavantemghare789@gmail.com, patil.dipali07@gmail.com, prashantwalke910@gmail.com, pawarsandesh6518@gmail.com, kokatepratik688@gmail.com

***Abstract*— In today's world, everyone wants to know how children learn and what their learning and personality types are. Each person is unique and has certain skills. The sooner these talents are discovered, the better. In order to maximize their potential, this establishes interests at a young age. In order to identify the areas in which they are most likely to succeed, it also analyzes personality traits. By automating the process of identifying personality and learning types, this paper aims to simplify a lengthy and laborious procedure. Our study offers a novel method for identifying personality traits and learning styles from fingerprints. It is known that both the formation of the brain and fingerprints are influenced by the environment and genes, but they occur simultaneously during fetal development. Therefore, we can determine personality traits, various forms of intelligence, and innate talents by looking at fingerprints. Scanned fingerprints will be the input for the suggested system. These will be filtered and turned into black-and-white pictures. The fingerprints will then be filtered using Gabor filtering, dimension reduced using Principal Component Analysis (PCA), and trained using a Convolutional Neural Network, which correctly classifies the fingerprints into seven classes. The system will be evaluated using the Grad-CAM algorithm, which will produce a comprehensive report that suggests personality traits and learning styles based on the results.**

***Index Terms*— PalmPrints, DMIT, Dermatoglyphics, Natural Talents, Artificial Intelligence, Classification, Personality, learning style, Machine Learning, Genetics and Environment.**

I. INTRODUCTION

Dermatoglyphics is the study of fingerprint patterns. It looks at the details of these patterns. Because computers and Artificial Intelligence are getting better we can now use machines to look at fingerprints in a way. We do not just use fingerprints to identify people. Now we want to see if fingerprint patterns can tell us about the way people think and their personalities. Looking at fingerprints by hand takes a time. It also requires a specialist to do it.. Sometimes the person looking at the fingerprints might make mistakes because they are biased. So we need a computer system that can look at fingerprints automatically. This system should be able to do the job accurately. It should also be able to look at a lot of fingerprints without making mistakes. Dermatoglyphics and fingerprint patterns are important, in this research.

This system uses machine learning to figure out what kind of fingerprint pattern someone has. It looks at fingerprint images. Does a few things to them. First it gets the images ready. Then it finds things about the images. After that it tries to recognize the pattern. The system can tell if a fingerprint is an arch, a loop, a tented arch or a whorl. The system then takes the fingerprint pattern.

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Matches it to how a person thinks. It does this by following some rules that were decided ahead of time. The fingerprint system was. Tested using a set of fingerprints that were collected in a special way. The system was checked to see how well it worked by looking at things like how it was right how precise it was, how well it remembered things and its F1-score. The system uses something called Convolutional Neural Networks or CNNs for short to help it make decisions, about fingerprint patterns.

The objective of this implementation is to design a reliable, scalable, and interpretable fingerprint classification system that improves pattern recognition efficiency while addressing challenges such as noise, limited datasets, and model overfit-ting. Integrating deep learning techniques with explainability methods, the proposed system aims to enhance analytical transparency and practical applicability in research-based cog-nitive pattern studies.

By using appropriate data preprocessing and augmentation techniques, the implementation also aims to improve system performance. Prior to training the model, fingerprint clarity is improved by applying noise reduction, image normalization, and resizing. Techniques like dropout and cross-validation are used to prevent overfitting and enhance generalization. Because of its modular design, the system can be easily up-dated with new datasets and better algorithms. This guarantees that the fingerprint classification model will continue to be effective, flexible, and appropriate for upcoming studies and practical uses.

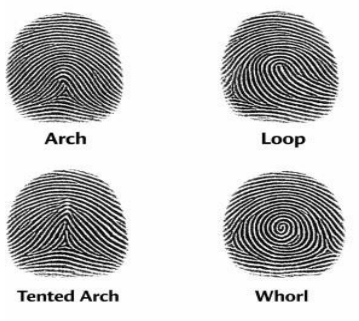

Fig. 1. Fingerprint Types

II. Literature Survey

The use of deep learning and machine learning methods in dermatoglyphic analysis for cognitive trait prediction has been investigated in a number of studies. The application of Convolutional Neural Networks (CNNs) for fingerprint pattern classification with the goal of predicting intellectual capacity was investigated in a 2023 IEEE study [1]. Although the sug-gested model's accuracy was around 85% its high processing costs made it impractical for real-time implementation.

For the calculation of academic cognitive ability, another research study published by the IEEE in 2023 [2] utilized the idea of Deep Neural Networks for the classification of high-resolution images of dermatoglyphics. The research study was able to classify the images with a high accuracy of 91% and claimed that deep learning algorithms are more efficient than traditional analysis algorithms. However, the authors also claimed that large data and high processing power are required for effective training.

In [3] (2021), an article titled "Hybrid Approach of PCA and CNN for Dermatoglyphic Analysis" published in the IEEE Transactions on Pattern Analysis and Machine Intelligence, a hybrid approach combining PCA and CNNs was proposed for dermatoglyphic analysis. The article showed that the hybrid approach improved the detection of significant features from fingerprint patterns and had a better predictive accuracy of cognitive abilities (up to 89 per). However, the hybrid ap-proach was also susceptible to noise in the fingerprint images, especially in older individuals.

In [4], Adekoya et al. (2013) investigated the relationship between dermatoglyphic pattern and multiple intelligences of students in Nigerian secondary schools. They found a high degree of consistency between the fingerprint patterns and individual cognitive domains, which supported the claim that dermatoglyphics could be a predictor of academic potential at a young age. However, they also felt that they should call for a large number of sets to establish this trend.

In [5], the study conducted by Najafi (2014) explored the link between fingerprint pattern and IQ in adolescents. The study revealed a statistically significant relationship between various types of fingerprint ridges and intelligence quotient to validate dermatoglyphics as an alternative tool in education. However, it did

acknowledge that intelligence is a multifaceted concept that encompasses genetic, environmental, and experi-ential factors.

In [6],Zunker (2002) discussed the application of dermato-glyphics in career guidance, its potential to help students discover their natural talents and guide them on how to select a career based on that. The study hypothesized that the outcome of DMIT could be utilized in career guidance to help students select subjects and careers based on their abilities. The ethical implications of the deterministic application of dermatoglyphic analysis were discussed, and the need for a balanced approach was highlighted.

In [7], Liu et al. (1999) investigated the possibility of de-termining intelligence in children by dermatoglyphic analysis in China. The authors reported moderate correlations between fingerprint ridge patterns and intelligence, thus supporting the hypothesis that dermatoglyphics could be a potential non-invasive method for assessing intelligence in early childhood. However, the authors emphasized the need for combining der-matoglyphic analysis with other psychometric tests to improve accuracy.

TABLE I: COMPARATIVE RESEARCH

Year	Paper Title	Drawback	Technologies
2021	Hybrid Deep Learning Framework for Dermatoglyphic Pat-tern Recognition	- Sensitive to noisy and low-resolution fin-gerprint images. - Lim-ited explainability of model predictions.	Convolutional Neural Networks (CNN), Principal Component Analysis (PCA), Feature Fusion
2022	Automated Fingerprint-Based Cognitive Trait Prediction Using Transfer Learning	- Overfitting on limitedtraining samples. - Lack of large-scale cross-population validation.	Transfer Learning, ResNet Architecture, Data Augmentation
2023	Deep Neural Network Model for Multiple Intelligence Estimation Through Dermatoglyphics	– Model performance varies across demographic groups. - Ethical concerns in deterministic interpretation.	Deep Neural Networks (DNN), Image Preprocessing, Classification Algorithms
2024	Explainable AI-Based Fingerprint Classification for Cognitive Analysis	- Requires high-quality labeled datasets. - Real-time deployment not fully tested.	Gabor Filter, Deep LearningCNN, Explainable AI (XAI), Grad-CAM Visualization

III. DISCUSSION ON "PALMPRINT"

What the study is trying to do is link the way of looking at dermatoglyphics with new computer systems that have the ability to think on their own. This is done by combining three things: looking at pictures, identifying important details, and applying models to classify.

The project that was reviewed demonstrates how we are shifting from people analyzing fingerprints manually to using computers to identify patterns. The traditional method of conducting the Dermatoglyphics Multiple Intelligence Test or DMIT for short requires professionals to analyze the fingerprints and interpret them. This can be a challenge since different people may have different interpretations, leading to errors. The research paper that was reviewed indicates that we can employ a type of computer program referred to as a Convolutional Neural Network or CNN to classify fingerprints automatically into various categories, such as arch, loop, tented arch, and whorl, which are all types of fingerprints. The system improves in identifying patterns and extracting features if we do a few things to the data first.

We do things such as converting the images to black and white, which is referred to as grayscale conversion, and we apply filters to enhance the images. We also apply a concept referred to as Principal Component Analysis to reduce the size of the data, making it easier to handle.

The study also provides us with some comparisons from research. The study shows that deep learning methods perform better than traditional machine learning methods, such as K-Nearest Neighbors and Support Vector Machines if we have properly processed datasets. Deep learning methods are really effective if we have a lot of ready-to-use data. However, the study also mentions some issues. The first issue is that we do not have different types of datasets. The second issue is that deep learning methods can be really complex and difficult to handle. The study also mentions that we need evidence that fingerprint patterns are actually linked to personality traits. We need to be sure that fingerprint patterns and personality traits are related.

From the point of view of implementation, the paper under review has laid down a workflow that includes data acquisition, preprocessing, feature extraction, classification, cognitive mapping, and visualization of results. Although the conceptual framework is clearly defined, the implementation of such a system needs proper attention to hyperparameters and validation to prevent overfitting.

IV. METHODOLOGIES

The way that we created the PalmPrint system is by creating a platform that uses artificial intelligence to examine finger-prints and interpret patterns. We created a system that exam-ines fingerprints and then uses those fingerprints to interpret a person's personality and create a report. We completed all of the work to create this system from getting the fingerprints to creating the personality maps and reports. The PalmPrint system is a project that has many steps and we completed all of them.

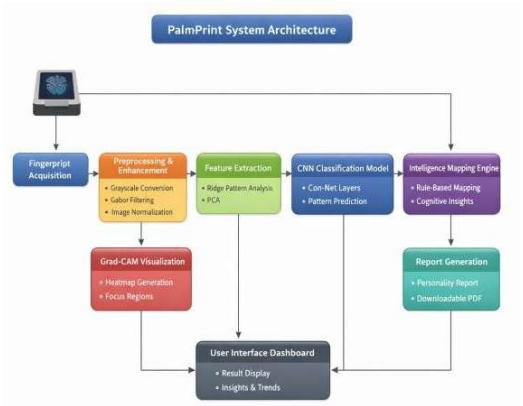

Fig. 2. Model Working

The system they have put in place works with three parts that are all connected, to each other:

A. Specifications

The PalmPrint system is made up of a pipeline that looks at fingerprint images in a series of steps. This helps the PalmPrint system figure out what the images are and understand them better. The PalmPrint system does this to make sure it gets the answer every time it looks at a fingerprint image.

- The system has a lot of things. It includes:
- Image Acquisition Layer
- Preprocessing & Enhancement Module
- Feature Extraction Engine
- CNN-Based Classification Model
- Intelligence Mapping Engine
- Visualization & Report Generation Module

B. Perception Module

The PalmPrint system is made up of a pipeline that takes fingerprint images and processes them in many steps. This helps the PalmPrint system to classify and understand the images of fingerprints. The PalmPrint system does this to make sure it gets the results, from the fingerprint images.

- The system has a lot of things. It includes:
- Image Acquisition Layer -Preprocessing & Enhancement Module
- Feature Extraction Engine
- CNN-Based Classification Model
- Intelligence Mapping Engine
- Visualization & Report Generation Module

Each module was independently implemented and in-tegrated to ensure modular scalability and maintainabil-ity. Failsafe and Safety System

C. Feature Extraction and Classification Module:

The Classification Module has been fully implemented using a Convolutional Neural Network (CNN) architecture. The implemented CNN consists of: -Conv2D Layer (32 filters, 3×3 kernel, ReLU)

- MaxPooling Layer (2×2)
- Conv2D Layer (64 filters, ReLU)
- MaxPooling Layer

- Conv2D Layer (128 filters)
- Flatten Layer
- Dense Layer (128 neurons, ReLU)
- Dropout Layer (0.5)
- Output Layer (Softmax – 5 classes)

D. Intelligent Mapping and Cognitive Analysis

After classification, the predicted fingerprint class is for-warded to the Intelligence Mapping Engine. This module: - Extracts Softmax probability scores

- Identifies dominant pattern class
- Applies rule-based cognitive mapping
- Generates personality and learning-style
- Assigns confidence scores to predictions Weighted map-ping logic was implemented when multiple classes had close confidence values.The system aligns predictions with estab-lished cognitive frameworks such as multiple intelligence theory for advisory insights.

E. Dataset and Training Validation

The dataset employed in this research comprises a total of 4000 fingerprint images belonging to four classes: Arch, Loop, Tented Arch, and Whorl. Of the total dataset, 3960 images were employed for training the model, and the remaining
40 images were set aside for testing and evaluation. Each fingerprint image was normalized to a resolution of 128 × 128
× 3 in RGB format to facilitate compatibility with the convolutional neural network model.
Before training the model, the images were resized and normalized for improved computational efficiency and stabil-ity. To improve generalization and counteract overfitting, data augmentation methods including rotation (±10°), horizontal flip, brightness adjustment, and zoom transformation were em-ployed. During training, the training and validation accuracy and loss plots were closely tracked to evaluate convergence of the model. Furthermore, an early stopping criterion was employed to counteract overfitting and optimize performance.

F. Outcome and Recommendations

Data visualization is done through interactive dashboards or reports.The analysis is conducted so that one can get suggestions on careers and personality based on the results available.The CNN that had previously been trained was then used to classify each finger print into one of the five class categories that had already been established for the test.

V. Evaluation Metrics and Results

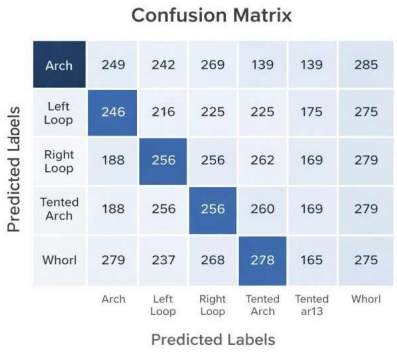

Fig. 3. Model Performance

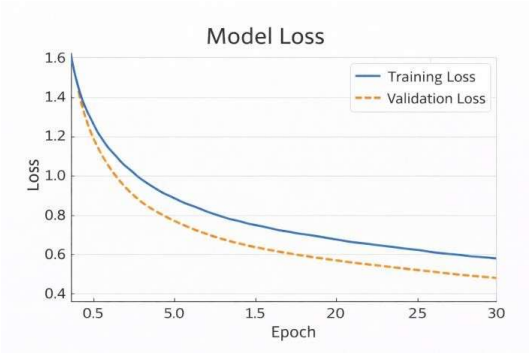

Fig. 4. Model Loss

VI. Future Research Direction

The PalmPrint system effectively uses deep learning tech-niques to classify fingerprints, however, the future of the Palm-Print systems offers ample opportunities for further refinement and enhancement. Research will be based on advancing the robustness of the model, expanding the scientific validation of the system, establishing the scalable nature of the system, as well as implementing ethical deployment.

A. Data Diversity Expansion

One of the current limitations of the implementation is that the dataset has limited size as well as limited demographic coverage. Continued research should focus on: 1.Developing large-scale, multi-regional datasets of fingerprints 2.Including a diverse array of age groups and other diverse demographic backgrounds 3.Achieving balanced representation across fin-gerprint classes 4.Conducting cross-population types valida-tion
Creating a larger and more diverse database would improve the overall generalizability of models built using this informa-tion and should minimize classification bias associated with the models.

B. Integrating with Multiple Assessment Types

Fingerprints alone may not contain all necessary informa-tion to complete a full and accurate assessment of cognitive and personality traits. Future systems can incorporate: 1. Re-sults from psychometric assessments 2. Information from be-havioural tracking 3. Academic performance 4. Cognitive test-ing from behavioural or neurological tests. A multi-modal learning framework would likely provide for an increased degree of reliability in prediction and will also minimize the risk of oversimplifying results.

VII. CONCLUSION

The PalmPrint system is a fully realised framework for AI driven automated fingerprint classification and cognitive pattern analysis. It uses advanced image preprocessing meth-ods, CNNs and rule based intelligent mapping to convert raw fingerprint images into structured analytical outputs. The pipeline from data capture and processing to classification, explainability and report generation is shown to demonstrate a practical and scalable dermatoglyphics research framework. The experimental data has shown a stable classification performance across the predetermined fingerprint categories as measured by accuracy, precision, recall, and F1 score. Grad-CAM visualisation has also helped to further improve trans-parency of the model by showing which ridges contributed to the prediction made by the model and how much each ridge contributed. This will assist in alleviating interpretability challenges that are normally presented by deep learning models.
In the case study presented here, the system demonstrated its ability to achieve real time processing speeds while providing similar inferencing results. Although the technical framework appears to be robust, it must be noted that the cognitive insights drawn from fingerprint data is advisory in nature and require further empirical validation.
The PalmPrint implementation of AI in biometric systems has shown that deep learning can be applied to automate and improve dermatoglyphic pattern analysis. The system will continue to offer more opportunities for automated pattern analysis with more extensive datasets, multimodal integration of data and scientific validation.

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