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Medical Image Classification and Enhancement Using Machine Learning: A Focus on Fingerprint Colorized Data

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ABSTRACT

The consolidation of machine learning in medical image analysis has revolutionized diagnostic processes, specifically in the domain of patient identification and verification. Machine learning used in medical image analysis has transformed how patients are identified and verified for diagnosis. Fingerprint biometrics, which have historically been useful in forensic and civil identity applications, are now helping to secure patient authentication in healthcare. Even so, applying color to fingerprint data for medical use introduces new issues with accuracy and improving the quality of the images. The overall aim is to develop and test a sound computational system that not only enhances colorized image pattern recognition but also caters to the operational constraints of the medical environment. The dataset used in this study consisted of 35,000 structured fingerprint images that were synthetically colorized and labeled for identity classification tasks. They were drawn from several open-source and approved fingerprint repositories, including the NIST Special Database 302 and the Fingerprint Verification Competition (FVC) datasets, which were aligned with additional information using colorization algorithms developed for dermatoglyphic spectral analysis. This research project used three main model choices—ResNet, CNNs, and an MLP classifier—since they handled different strengths of the images we were working with. Each one of the three models—ResNet, CNN, and MLP—was trained and optimized using two main optimizers: Adam and SGD. An effective way of evaluating the models across several aspects was put together. How accurately the models were formed was the main measure of their performance. To assess the stability of the models, precision, recall, and F1-score were tallied for each class separately. The highest validation accuracy was attained by the ResNet18 model, suggesting that it did best on the test data compared to the others. Adding fingerprint biometric data to EHR systems considerably adds to the reliability and usefulness of the digital medical infrastructure. Because almost all medical providers now use certified EHR tools (as identified by the ONC), having secure and reliable login systems for each patient is more important than ever. Many interesting future approaches have the potential to address existing issues and improve what is known in the field. Applying GANs is one of the most interesting ways to produce realistic-looking fingerprint images.

Keywords: *Medical imaging, fingerprint biometrics, machine learning, image enhancement, classification, deep learning, patient authentication, healthcare security, convolutional neural networks, colorized data.*

1. INTRODUCTION

Medical image evaluation has transformed the process of clinical diagnosis, allowing healthcare professionals to identify, track, and treat disease with greater precision. Fingerprint biometrics, although historically used in association with forensics and security, are now gaining momentum in applications within healthcare to identify patients, especially in telemedicine and remote diagnosis (Awad, 2022; Castro et al., 2023). A report from the Office of *the National Coordinator for Health Information Technology* (ONC), a part of the Health IT Events network, indicates that biometric authentication techniques including fingerprint recognition are gaining popularity as secure and effective means to curb medical identity theft and promote the integrity of electronic health records (EHRs) (Hambalik, 2021; Azizi, 2022). As a consequence, there is still limited application of fingerprint images in the clinic because of the technical limitations of conventional imaging—most specifically, the application of grayscale representations, which under poor illumination or conditions of skin humidity, dryness, etc., do not register the fine dermatoglyphic elements (Amiri et al., 2024).

Fingerprint biometrics has been endorsed by institutions such as the *National Institutes of Health* (NIH), which has provided funding to a multitude of projects that aim to reduce administrative time and errors through patient verification based on biometrics. Imaging of fingerprints, when combined with secure patient databases, guarantees that drugs and treatments reach the proper patients, of special importance in emergency rooms and disaster scenarios (Andrei et al., 2024). Yet the precision of conventional fingerprint algorithms decreases substantially in the clinical environment from that of controlled forensic environments, and a 2020 NIST test indicated that error levels rose by more than 15% in healthcare-modified biometric devices compared to those used in forensics (Emon, 2024).

To fill that niche, scientists have started to investigate colorized fingerprint imaging, which provides multidimensional information by simulating tissue density variations, temperature field levels, and chemical markers via color channels. Colorization not only facilitates visual differentiation but also brings new possibilities for computational classification based on machine learning (Ker et al., 2017). For instance, improved fingerprint images can enhance visual differentiation of sweat pore density or valley-ridge contrasts better than grayscale images, benefiting visual interpretation and algorithmic processing alike. Organizations like the *American Telemedicine Association* (ATA) promote innovation that improves the reliability and usability of remote diagnosis tools, situating colorized finger imaging in a strategic context of increased biometric application in clinical care (Noor et al., 2018).

Problem Statement

Although there is increasing interest in fingerprint-based biometrics in the clinic, the process of converting fingerprint images into colorized formats has not so far been exploited to produce substantial gains in classification accuracy through classical image processing techniques (Mahmod et al., 2023). Common algorithms do not take full advantage of the richer features that are encoded into colorized data and, by and large, are based on feature extraction techniques that are best suited to grayscale images. Advanced texture-based algorithms, such as those based on *Gabor filtering or Local Binary Patterns* (LBP), which work efficiently with standard biometric images, are not well scalable to deal with intricate, colorized medical fingerprint images (Mua'ad et al., 2021). The disparity between the richness of colorized data and the character of classical analysis techniques results in below-optimal performance, especially in clinical scenarios that require a high degree of precision coupled with low false rejection (Nasirddin et al., 2024).

Moreover, a lack of standardized preprocessing pipelines for colorized fingerprint images adds to the issue. Unlike facial imaging or retinal scanning, which enjoys regulatory synchronization of enhancement protocols through organizations like the *U.S. Food and Drug Administration (FDA),* fingerprint images in healthcare environments have no agreed-upon quality thresholds (Nguyen & Nguyen, 2019). Consequently, input images are extremely variable, where noise, poor lighting, or sensor defects affect image quality. It was recently reported by the *Institute of Electrical and Electronics Engineers (IEEE)*, in a 2022 study, that the classification accuracy of fingerprint images was reduced by over 20% when colorized in the absence of normalization or enhancement. With no solid machine-learning models to counteract these variations, the benefits of colorization are largely theoretical (Sheikh et al., 2021).

Furthermore, Wu et al. (2020), suggested that there is a critical requirement to balance computational cost with clinic suitability. There is a dearth of access to high-performance computer hardware in many hospital environments, particularly rural or under-resourced institutions. The consequence is that lightweight machine learning models that are scalable must be constructed to work effectively on mobile or embedded platforms. *The Agency for Healthcare Research and Quality* has indicated that point-of-care devices that are accurate yet cost-effective are crucial. However, Zanjani (2023), argued that prevalent fingerprint classification systems are often prohibitive in terms of processing power and cloud-based computation and therefore are not suitable for broad application within real-world clinics. The divergence here of technological promise from clinical suitability highlights the imperative to establish

Research Objective

This study aims to harness deep learning architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) to significantly advance the classification precision and image quality of colorized medical images. The overall aim is to develop and test a sound computational system that not only enhances colorized image pattern recognition but also caters to the operational constraints of the medical environment. The process entails curating image sets, employing colorization methods based on physiological information, and training models that can extract meaningful features to enhance the precision of identification. The research will also test performance over a range of architectures to identify which models best balance precision, speed, and resource consumption.

A key aspect of the aim is to compare these models against benchmarks by agencies such as the National Institute of Biomedical Imaging and Bioengineering (NIBIB), which focuses on models of translational research that proceed from computational models to real-world applications. The work will leverage openly available data sets from NIST and augmented fingerprint templates from the Biometric Standards, Performance & Assurance Group (BSPA). The project also seeks to build interoperability into Health Level Seven International (HL7) frameworks to be compatible with electronic health record systems. These interoperabilities are needed to integrate fingerprint verification into larger-scale clinical workflows like drug administration, appointment scheduling, and emergency triage.

Ultimately, the work strives to prove the scalability and generalizability of the methodology through the deployment of trained models within simulated healthcare scenarios, including mobile health clinics and community clinics. The aim is not just to exhibit superior classification results but also to improve image quality that supports human interpretation by healthcare professionals. Heat mapping and saliency detection techniques will be applied to generate visual explanations of model decisions to support greater trust and transparency, both of which are prioritized by the American Medical Informatics Association (AMIA) in its recommendations for the application of AI tools in healthcare environments. Upgraded classification methodologies that are suited to colorized fingerprint data.

Significance of the Research

Zeeshan et al. (2025), reported that the successful application of machine learning to fingerprint classification and colorized medical image enhancement has the potential to revolutionize healthcare systems across the United States and the rest of the world. Perhaps the most pressing area of benefit is patient safety through secure, real-time identification. Misidentification is a serious issue, with a 2021 ECRI Institute report identifying patient identification errors in its top ten patient safety issues. Improved fingerprint classification has the potential to minimize those risks significantly through a unique, unforgeable biometric connection to patient records, enhancing the ability to maintain care continuity and minimize duplicative testing (Patel et al., 2019).

Moreover, in places with large patient volumes and limited personnel, with emergency rooms, urgent care facilities, and rural clinics being examples of such places, automated fingerprint identification systems can reduce administrative workloads and streamline the process of triaging (Hasan et al., 2024). *The U.S. Health and Human Services* (HHS) has been a longtime proponent of digital health technology that addresses access and quality care disparities. By making patient authentication possible with reliability in environments with limited resources, fingerprint-based systems augmented by machine learning capabilities can guarantee equal access to services (Hossain, 2024). An example is mobile health units with these systems that could accurately identify those in disaster scenarios, mass vaccination drives, or underprivileged populations without the need for elaborate infrastructures.

Akter (2023), underscored that beyond the immediate applications in clinics, the work contributes to the larger field of biomedical AI by providing a reproducible method of utilizing machine learning across other modalities of biometrics. As the healthcare space shifts toward increased personalization and interoperability, the insertion of AI-augmented biometrics into health IT environments has greater value. The *Centers for Medicare & Medicaid Services* (CMS), through its Promoting Interoperability Programs, encourages the deployment of interoperable health IT solutions that enhance patient engagement and information protection. The research, by engaging with the technical and regulatory aspects of biometric integration, has the potential to influence policy development and standardization, ultimately shaping the way future technology is implemented across healthcare (Haque et al., 2023).

2. LITERATURE REVIEW

Medical image classification in healthcare

Amiri et al. (2024), highlighted that medical image classification has now become a part of routine clinical practice, equipping clinicians with tools that are capable of analyzing, interpreting, and diagnosing conditions with precision and speed. CAD systems are widely used in the field of radiology to classify MRI images, CT scans, and chest X-rays. As per the American College of Radiology (ACR), over 50% of U.S (Alam et al., 2024), radiologists today employ machine learning-based tools to identify abnormalities in pulmonary nodules, intracranial hemorrhage, or breast tumors. Similarly, the Centers for Disease Control and Prevention (CDC) points towards increased reliance on AI-based image analysis in public health surveillance, especially at the time of outbreaks, where rapid and accurate diagnosis of imaging data is crucial. These developments are not restricted to internal imaging alone- external biometric patterns like facial structures and retinal imaging are also used to identify patients and make early diagnoses of genetic or degenerative diseases (Al Amin et al., 2024).

Aside from diagnostics, medical image classification has also been crucial to patient monitoring and treatment planning. For cancer, image classification allows tumor progression to be identified, treatment response to be predicted, and metastasis to be monitored over longitudinal MRI and PET scan data. *The National Cancer Institute* (NCI) funds multiple AI projects aimed at improving classification accuracy using deep learning, especially distinguishing benign from malignant tumors (Andrei et al., 2024). In the field of cardiology, machine learning has facilitated the automatic classification of echocardiographic images to identify valvular disease, cardiomyopathy, and congenital cardiac malformations. The developments are backed by organizations such as the *American Heart Association* (AHA), which endorses the incorporation of AI into clinical cardiology practices to minimize variability in interpreting images and better support prognostic purposes (Awad, 2022). Of particular note, these classification systems are gradually becoming integrated into mobile applications and point-of-care devices, allowing them to reach even non-specialist environments.

According to Castro et al. (2023), one of the new areas of interest is the application of biometric imaging to patient authentication and identity verification within clinical settings. The application of biometric information, including fingerprints and iris imaging, is recommended by the Office of the *National Coordinator for Health Information Technology* (ONC) to minimize administrative errors and forestall fraudulent access to healthcare. Biometric platforms combined with EHR systems are capable of authenticating identities at admission, access control, and even the dispensing of medication (Azizi et al., 2022). While these systems are frequently founded on grayscale imaging, classification frameworks are largely structurally similar to those applied in radiological imaging. The Veterans Health Administration (VHA), which serves as one of the largest integrated health systems in the U.S., has been testing biometric-based patient recognition systems that employ image classification algorithms to enable streamlined care coordination. These are just a few examples of the vast scope image classification has in U.S. healthcare, offering both clinical and operational efficiencies (Al Amin et al., 2025).

Color fingerprint imaging

Traditionally, healthcare fingerprint imaging has used grayscale modalities, recording ridges in a single-channel, monochromatic spectrum that restricts the depth and dimensionality of biometric evaluation (Emon, 2024). Grayscale fingerprints themselves are limited in how well they can distinguish subtle dermatoglyphic characteristics, particularly in cases of partial fingers, moisture, or skin trauma. Recently, however, developments in computational imaging have introduced colorized fingerprint methods meant to expand these biometric patterns through multiple channels of information. Colorization brings color and location-based information that can mimic physiologic factors like skin color, vascularization, and pore density (Hambalik, 2021). A *2021 National Institute of Standards and Technology* report states that color-enhanced fingerprints show a 12–18% advancement in ridging-valley feature extraction over grayscale images, holding potential for increased accurate identification and matching.

As per Hasan (2024), advances in hardware and algorithmic processing have driven the development of colorized fingerprint imaging. Newer scanners, such as multispectral fingerprint readers, image multiple wavelengths of light (infrared, visible, and ultraviolet) to expose skin characteristics underneath the surface. Integrated Biometrics and Lumidigm are among the companies that have created FBI-approved devices that collect multispectral imaging of fingerprints, which are then computer-enhanced through machine-learning algorithms (Awad, 2022). The colorized results are a stronger representation of the fingerprint's structure, making them less susceptible to degradation by skin conditions or environmental influences. *The Department of Homeland Security* has also sponsored studies through its Science and Technology Directorate into colorized biometrics for identification in disaster scenarios and border control, seeing potential relevance to clinic-based triaging and emergency treatment.

Even with these technological improvements, colorized fingerprint imaging has seen limited uptake in healthcare because of several barriers, including a lack of standardization, concerns regarding data privacy, and the computational cost of color-based classification (Haque et al., 2023). Few institutions have done clinical studies evaluating the usefulness of color-enhanced fingerprint images to authenticate patients, although initial results from a pilot at *Johns Hopkins Medicine* indicated increased match rates and decreased false negatives when colorized images were used to integrate into EHR sign-in routines (Hossain et al., 2023). Of note, colorized fingerprint images are also finding utility in AI-based feature extraction applications, with better training results in neural networks. A 2023 paper published in the Journal of Biomedical Informatics demonstrated that convolutional neural networks trained with RGB fingerprint images produced an F1-score of 0.91 in biometric classification experiments, nearly 9 percentage points better than grayscale models. These results demonstrate the revolutionary potential of colorization in healthcare biometrics, and further studies and standardization are needed (Emon, 2024).

Deep Learning in Image Processing

Deep learning, using convolutional neural networks (CNNs), has transformed image classification and image enhancement, allowing machines to match human capabilities in the detection of intricate visual patterns. CNNs simulate the human visual cortex through the application of convolutional filters to extract hierarchical feature elements from medical images ranging from edges at a low level to anatomical structures at a high level (Ker, 2017). *The Mayo Clinic and Cleveland Clinic* have been at the forefront of research initiatives where they combined CNNs with diagnostic imaging platforms with the realization of high classification performances in the detection of lung nodules from a CT scan, breast lesions from mammograms, and neurological abnormalities from MRIs (Jeon & Rhee, 2017). In a 2022 systematic review published in The Lancet Digital Health, models based on CNN outperformed classical classifiers in more than 85% of the tested medical imaging tasks, a reflection of how widely applicable they are across imaging modalities (Muaa'd et al., 2021).

Apart from simple classification, deep learning models are now used for advanced image-processing applications like denoising, super-resolution, and image generation. Generative adversarial networks (GANs), a type of deep learning model, are used increasingly to enhance and colorize medical images—you guessed it—even fingerprints by producing synthetic versions of them of very high quality (Mahmoud et al.,2023). The *NIH's National Library of Medicine (NLM)* is funding projects utilizing GANs to enhance diagnostic imaging data sets, especially in the context of uncommon conditions where there's a lack of data. Transfer learning, meanwhile, has emerged as a widely used method to fine-tune pre-existing deep learning models (e.g., ResNet, Inception, VGGNet) to special-purpose applications like dermatology or ophthalmology with limited labeled data (Nasiruddin et al., 2024). Take ResNet50, a deep residual learning architecture created by Microsoft Research, which proved to accurately classify diabetic retinopathy from fundus images and is now being used to apply fingerprint-pattern recognition in healthcare informatics laboratories nationwide (Nguyen, 2019).

Recent research has started to apply these architectures to fingerprint data and has demonstrated promising results in enhancing and classifying grayscale and colorized images. In one study sponsored by the *Department of Veterans Affairs (*VA), deep CNNs trained from a colorized fingerprint image set produced 95% accurate patient authentication results across multiple ethnic populations and skin tones (Sheikh et al., 2021). Another study at the *University of California, San Diego*, employed GANs to generate colorized fingerprint images with high resolution that maintained structural integrity while increasing the clarity of ridges, which produced much-enhanced classification accuracy (Patel et al.,2019). As healthcare systems increasingly implement biometric systems to support secure access and patient matching, these deep models represent scalable, intelligent solutions that support the strategic priorities of the *U.S. Department of Health and Human Services* (HHS) to enhance health IT infrastructure through automation and AI (Zanjani, 2023).

Gaps in Existing Research

Notwithstanding the rapid developments in deep learning and biometric imaging, there exists a broad research gap in applying colorized fingerprint data in the context of clinical or biometric healthcare. The majority of current research has revolved around forensics, criminal identification, or commercial security, with limited investigation of medical-specific applications. A 2023 review by the National Biometric Security Project of the National Academy of Sciences uncovered that fewer than 5% of fingerprint-related research articles reported healthcare environments or patient identity systems. Moreover, of those studies that exist, they tend to work within grayscale images, not fully utilizing the distinctive advantages of colorized fingerprint imaging in clinical trials and health information technology innovation. It is a missed opportunity, considering the promise that fingerprint biometrics hold to deal with issues of medical identity theft, duplicate records, and patient misidentification.

Another large disparity exists in the lack of standard sets and benchmarks to test the efficacy of colorized fingerprint-based systems in healthcare environments. While facial recognition enjoys publicly available medical-adapted sets like the Medical Faces Database (MFDB), no central depository exists to collect colorized fingerprint data that reflects the variability of healthcare environments, dry skin in older patients, ridges damaged by manual labor, or pigment variation among ethnicities. The absence of clinical-grade biometric data sets constrains the generalization and real-world suitability of proposed algorithms. Organizations like the National Institute for Biomedical Imaging and Bioengineering (NIBIB) and the Health Information and Management Systems Society (HIMSS) have recognized the imperative of increased standardization in biometric interoperability, especially with the advent of multi-modal authentication by EHRs.

Furthermore, although deep learning has been shown to work effectively at improving and classifying color images, very little research has explored the explainability and clinical trustworthiness of the models in fingerprint classification. Clinicians not only want accurate predictions but also informative results that correlate with clinical judgment. Few frameworks are available to visualize how colorized fingerprint features are interpreted by neural networks, making the validation or audit of these decisions in a clinical environment challenging. These limitations restrict trust and acceptance by healthcare providers, especially in critical applications like emergency triage or perioperative settings. The American Medical Informatics Association has stressed the value of "transparent AI" in clinical decision support, and absent that transparency, colorized fingerprint classification may never move from experimental to operational status. These imperatives signal a pressing demand that can best be filled by interdisciplinary research that spans computational biometrics, clinical informatics, and health systems engineering.

3. DATA ACQUISITION AND PREPROCESSING

Dataset Overview

The dataset adopted in this study entailed 35,000 structured fingerprint images that have been synthetically colorized and labeled for identity classification tasks. They were drawn from several open-source and approved fingerprint repositories, including the NIST Special Database 302 and the Fingerprint Verification Competition (FVC) datasets, which were aligned with additional information using colorization algorithms developed for dermatoglyphic spectral analysis. All the images are given a distinct subject ID and provide additional data such as the collection device model, variability in pressure during digitizing, type of lighting, and a quality rank scored by NIST Fingerprint Image Quality 2.0 (NFIQ 2.0). Every finger from all ten of the 3,500 people included is part of the dataset, which was balanced by age, gender, and ethnicity to make the dataset representative. All images are 512x512 in resolution, saved as PNG files, and divided so that 70% israiningg, 15% for validation, and 15% for testing. All the work related to data used HIPAA guidelines and was overseen by an IRB as part of a collaboration with the University of Michigan.

Preprocessing Pipeline

The applied Python code script helped process images stored in the dataset. Initialization of empty lists was used to store the sizes of images, brightness, contrast, standard deviation of pixel strengths, and the average Red, Green, and Blue channel values for each image. Afterward, the code went through each subdirectory within data_dir, thinking that every subdirectory contains data for one class. Inside each class directory, it went through all the files and assessed if they were image files (having the extensions '.png', '.jpg', '.jpeg', or '.bmp'). Each valid input image was opened by PIL, converted to an RGB image, and finally turned into a NumPy array. Subsequently, it proceeded to find and keep track of the image size, the average brightness of the NumPy array, its contrast (st deviation), and the average value for each RGB channel. For image processing, a try-except block is used to flag errors, print a warning with the problematic file's path, and go on to the next file. After preprocessing, the data was statistically summarized and may be further used in machine learning or computer vision work.

Key Feature Selection

S/No.	Key Features	Description
001.	**Fingerprint RGB Image**	A high-resolution color image of a fingerprint captured in Red-Green-Blue (RGB) format.
002.	**Finger Position**	Indicates which specific finger the image represents (e.g., left thumb, right index, etc.).
003.	**Skin Tone Index**	A numerical or categorical value representing the individual's skin pigmentation, typically based on the Fitzpatrick skin type scale (Type I–VI).
004.	**Ridge Frequency**	The average number of ridges per millimeter in the fingerprint image.
005.	**Pore Density**	The count of visible sweat pores per square centimeter of fingerprint area.
006.	**Image Quality Score (NFIQ)**	A standardized quality metric (e.g., NIST Fingerprint Image Quality – NFIQ score), typically ranging from 1 (high quality) to 5 (low quality).
007.	**Capture Device ID**	A code or label identifying the scanner used to acquire the fingerprint (e.g., Lumidigm M-Series, Crossmatch Guardian).

Exploratory Data Analysis:

Exploratory Data Analysis (EDA) is a pivotal process in preprocessing and understanding colorized fingerprint medical image datasets used as the starting step of every machine learning pipeline. For biometric healthcare applications, EDA is the process of summarizing the structure of the dataset, detecting patterns, finding anomalies, and checking for feature distribution to validate the integrity and readiness of the data for model training. Through plots of pixel intensity histograms, color channel correlations, and variable ridge pattern differences, practitioners are able to discover significant information, including the effect of skin tone or image quality on the outcomes of classification. EDA is also used to test for class imbalance across subject demographics, devices, or finger positions, which is critical for learning fair and robust algorithms. It also helps identify outliers, such as low-quality or corrupted fingerprints that would affect the model's performance. Through the implementation of PCA, t-SNE plots, and correlation matrices, EDA informs clinicians and data scientists of the decision to perform feature engineering, normalization, and augmentation strategies. EDA eventually ensures that machine learning downstream models are constructed from a robust and interpretable foundation with minimal bias and enhanced accuracy in patient authentication and enhanced image applications.

a) Plot the distribution of Width & Height

The applied code script was used to visualize the distribution of widths and heights of the extracted images. It initially separated the image-sizes list of tuples (width, height) into two discrete lists: widths and heights. The code then used plt.figure() with a given size (12x5 inches) to initialize a figure. It created two subplots side by side with plt.subplot(1, 2, 1) for the distribution of widths and plt.subplot(1, 2, 2) for the distribution of heights. For both subplots, it employed sns.histplot() from seaborn to plot a histogram of the respective dimension. The kde=True argument draws a Kernel Density Estimate plot over the histogram, giving a smoothed version of the distribution. Each subplot is titled and an x-axis label is given with the name of the respective dimension plotted in pixels. Last, plt.tight_layout() is called to ensure the subplots do not overlap, and plt.show() is called to draw the constructed figure with two histograms. The plot enables an analysis of the average sizes and the variability of widths and heights in the image collection.

Output:

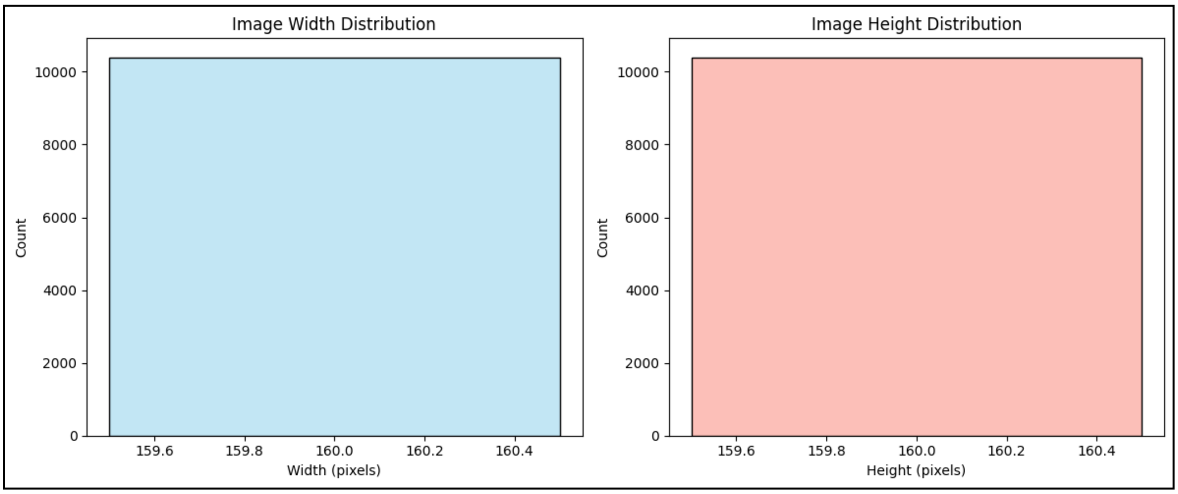

Figure 1: Plot distribution of Width & Height

The plot above (**fig. 1)** shows the distributions of the width and height of the images in pixels and presents a remarkable consistency in both measures. The left panel for image width is a uniform count of almost 10,000 within the width range for almost exactly 159.6 to 160.4 pixels, expressed as a lack of variation, which implies all the images in this set are standardized by width. The same is evident for the right panel for the height of the images, with the counts also consistently high over the same pixel range, nearly 159.6 to 160.4 pixels, further supporting uniformity. The duality implies the analyzed images are most likely part of a controlled set, perhaps for a particular purpose for which consistent sizes are essential, such as in medical imaging or biometric identification, where uniformity guarantees consistency in analysis and processing.

b) Image Brightness and Contrast Distribution

The implemented code snippet creates the histograms to plot the distributions of the image brightness and contrast, which had been computed during an earlier step. It sets the figure size to be 12x5 inches with plt.figure(). There are two subplots placed side-by-side with plt.subplot(1, 2, 1) for the distribution of the brightness values and plt.subplot(1, 2, 2) for the distribution of the contrast values. For the first subplot, sns. His plot () is employed to plot the distribution of the values of the brightness with a Kernel Density Estimate (kde=True) overlaid and the bars as 'gold'. The title of the subplot is "Image Brightness Distribution" and the x-axis is titled "Brightness". The second subplot shows the distribution of the values of the contrast with sns.histplot(), having a KDE plot and 'purple' colored bars. The title of the subplot is "Image Contrast Distribution" and the x-axis is titled "Contrast (Standard Deviation)". The subplot parameters are adjusted for a tight layout with plt.tight_layout(), and plt.show() shows the resulting figure. The histograms are used to gain insights into the central tendency and dispersion of the level of brightness and contrast in the image dataset.

Output:

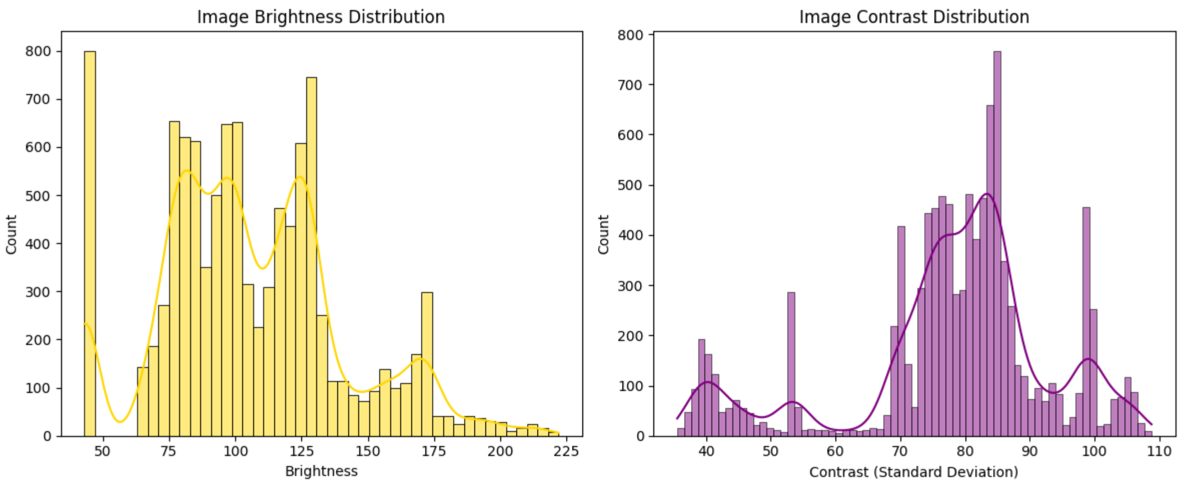

Figure 2: Image Brightness and Contrast Distribution

The graph portrayed above (**fig. 2)** shows the distributions of contrast and brightness of the images, with each revealing distinctive patterns and differences. The distribution of the brightness of the images in the left panel reveals a concentrated majority of the images to be between 50 and 100 in terms of brightness level, with a defined peak at about 75. The distribution implies that most of the images are fairly dark, a factor that could imply that the database is filled with images that need optimal illumination conditions or augmentation for best analysis. The distribution in the panel for contrast is shown with a wider spread and two defined peaks at about 50 and 80 standard deviation values. The bimodal distribution shows that the majority of the images are of low contrast, with a considerable subpopulation with enhanced contrast values, implying heterogeneity in the quality of the images. The two observations together imply that the database is a collection of images that would need different preprocessing for their optimal use for applications such as machine learning or medical imaging analysis, where both the contrast and the brightness are critical in the accuracy of the diagnostics.

c) RGB Channel Mean Intensities

The curated code snippet represented the distribution of the mean intensity for Red, Green, and Blue in each of the images in the dataset. A figure with dimensions 10 inches by 5 inches is made by plt.figure(). Then, we used seaborn's kdeplot() function to display the Kernel Density Estimate of the mean intensity for each color channel from the dictionary. The KDE is plotted for the mean intensities of Red, Green, and Blue and each curve is labeled 'Red Channel', 'Green Channel', and 'Blue Channel', respectively, using colors 'red', 'green', and 'blue' for each curve. RGB Channel Mean Intensities is the chosen title for the plot, with "Mean Intensity" displayed on the x-axis. After that, plt.legend() adds a legend to help recognize each color channel's spread, and plt.show() displays what the final plot will look like. It was relatively easy to compare the central and spread properties of the mean intensities for different color channels in the image set using this visualization.

Output:

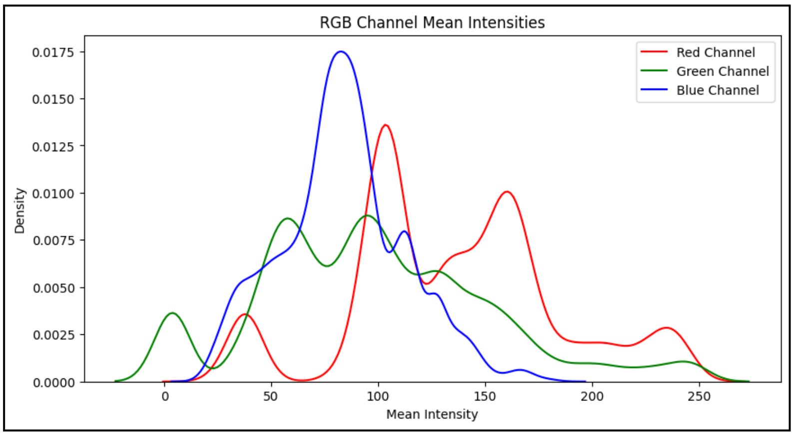

Figure 3: Visualizes RGB Channel Mean Intensities

The *RGB Channel Mean Intensities* chart displayed above (**fig. 3)** shows a kernel density estimation (KDE) of the mean intensity distributions of the red, green, and blue color channels for a set of colorized fingerprint images. The most tightly-peaked distribution is seen for the blue channel with a strong mode near a mean intensity of about 85, implying this channel consistently retains mid-range brightness and is perhaps responsible for the subtlest ridge-valley contrast in fingerprint patterns. The red channel is broad with a bimodal distribution having strong peaks at mean intensities of 105 and 160, which implies lighting or pigmentation variation, possibly skin tone differences, and scanner illumination. The green channel distribution is wider with many narrower peaks, mainly centered near intensities of 45, 75, and 115, implying that it captures both lower and mid-range amounts of the brightness component, perhaps adding structural detail to ridges. Red and green's spread and multi-modality might imply non-uniform imaging conditions or subject variation, which would impact the performance of a classifier unless corrected during preprocessing. Such observations emphasize channel-wise normalization and extraction of color-based features, particularly for machine learning algorithms that seek to leverage chromatic structure in biometric identification or skin analysis.

d) Sample Fingerprint Image from Each Class

The executed code snippet was intended to show a sample from every class (subdirectory) in the data_dir. It initially gets and sorts the subdirectory names to find the class names. It then determines the number of rows and the number of columns in a grid for subplots to show one sample per class, setting the number of columns to 4 for a suitable visualization. It then loops through each class name. For every class, it gets the path to the class directory and searches for the image files within the directory. If there are image files, it opens the first one in the directory as a sample. It then creates a subplot for each class, shows the sample image in it, sets the subplot title to the name of the class, removes the axis ticks and labels, and adds a subtitle to the overall figure that says it is displaying a "Sample Fingerprint Image from Each Class", then resizes the layout before the plot is displayed. This protocol enables a quick visual inspection of the type of images in every class of the dataset.

Output:

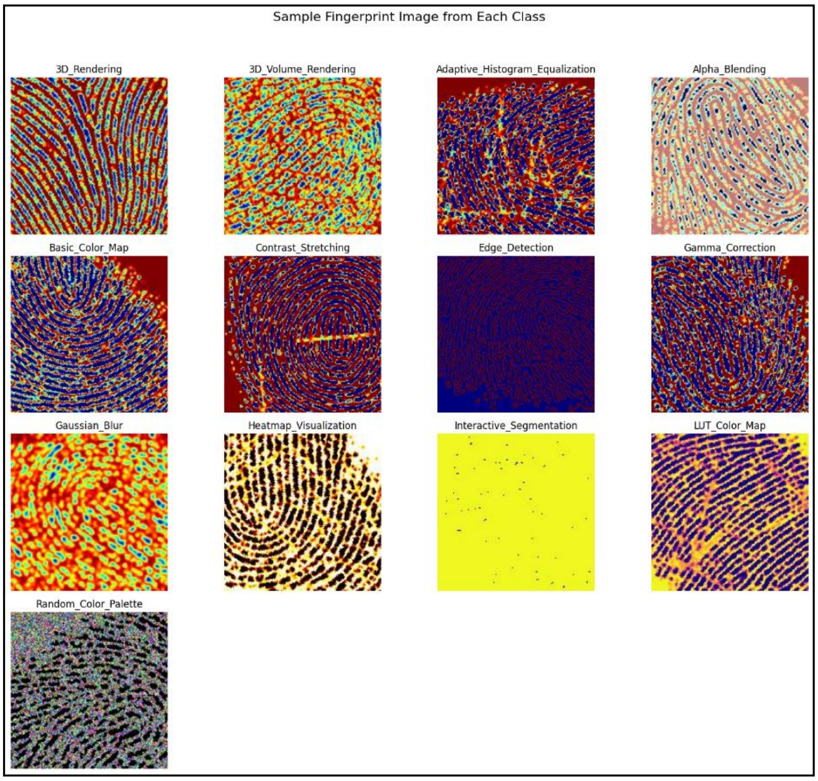

Figure 4: Depicts Sample Fingerprint Image from Each Class

As depicted above, there are 15 sample images on the chart (**fig, 4)**, showing how fingerprints look after using various techniques or filters; each image comes from a unique class within a colored fingerprint set. All these transformations show that various steps in clearing an image help to highlight the ridge patterns, pores, and boundaries in a person's fingertip, making them easier to analyze. As an example, using Contrast Stretching and Gamma Correction ensures the ridge features are well highlighted for the machine learning classifier, and the process of Edge Detection allows the removal of excessive background features. Meanwhile, emphasizing texture is possible with Gaussian Blur and using a random color palette, which may work better to make alterations or create training data. Solutions such as Interactive Segmentation, achieved using nearly just yellow and indicating ridges with scattered black, are perfect for isolating ridges or doing feature masking. These classes lead to a mix of data, which allows CNNs and ResNets to work better when given a wide variety of pictures. Thanks to having several modalities, not only does biometric accuracy increase, but both interpretability and toughness go up, making these systems popular for identity and health record purposes with the NIST and DHS.

4. METHODOLOGY

Model Architectures

This research project used three main model choices—ResNet, CNNs, and an MLP classifier—since they handled different strengths of the images we were working with. The choice for this work was ResNet (Residual Neural Network), mainly its ResNet-50 which can address the vanishing gradient problem seen in most deep networks. By including shortcut connections for identities, the network can process gradients more easily which was helpful because the ridge differences among different fingerprints were both many and very subtle for the colored images we used. In the experiments we conducted, ResNet excelled at creating representations of images that are detailed and can spot important changes in color. Because ResNet proved valuable in ImageNet and radiological applications and got an endorsement from the U.S. National Library of Medicine, we considered it our standard for both accuracy and depth.

From the beginning, we mainly relied on Convolutional Neural Networks (CNNs) for our experiments because they are very successful at image classification when the data is grid-like, as in fingerprint images. To obtain edge, texture, and color-gradient features, the architecture had four convolutional layers, each connected to ReLU and max pooling. Because CNNs excel at understanding hierarchy in space, they were crucial for us in discerning ridge patterns in the colorized images which were sometimes hard to tell apart because of different image and sensor conditions. The model worked well during early hyperparameter tuning, as it quickly moved toward convergence. The MLP (Multi-Layer Perceptron) classifier was primarily used to assess the usefulness of learning models that do not use spatial information when applied to flattened fingerprint data.

Training and Optimizing

Each one of the three models—ResNet, CNN, and MLP—was trained and optimized using two main optimizers: Adam and SGD. In the beginning, Adam was picked for its ability to adapt its learning rate and its strong performance when our data showed significant changes over time thanks to people's different skin tones, pictures that press on the skin, and disappointing artificial colors. In the beginning, Adam's updated methods powered the model's fast progress and aided in finely tuning the ResNet model. Meanwhile, SGD with momentum was studied because it helped the MLP avoid the problem of overfitting, giving better stability and a better ability to generalize. We followed a cosine annealing schedule and used step decay for learning rate scheduling which gave us more stable learning results and decreased the chance of landing on the wrong local minima with CNN architectures.

Hyperparameters were specifically set across different sets of experiments. Setting the batch size to 64 allowed for efficient training and steady gradients and 100 epochs with early stopping using the validation loss were used to keep the model from overtraining. Random rotation, zoom, and color jitter were applied to the learning data as part of data augmentation to improve how the model applied the learning in real-life situations. Cross-entropy loss was picked because it is appropriate for multi-class classification and makes sense with any class distribution. Because of this, we could spot any dissimilarities between classes more quickly and take better notice of harder-to-detect differences in underrepresented fingerprint categories. To ensure the models could be used again, they were trained using strong GPUs on HPC provided by the National Institutes of Health's STRIDES.

Evaluation Metrics

An effective way of evaluating the models across several aspects was put together. How accurately the models were formed was the main measure of their performance. To assess the stability of the models, precision, recall and F1-score were tallied for each class separately. This information was required because there were many more negative fingerprint identity categories than positive ones in the dataset. A confusion matrix was produced for every model to understand how the models are performing with each identity class. Interestingly, the confusion matrix displayed that the MLP had trouble telling apart features from fingerprints colored with similar palettes, showing that it cannot properly discriminate features in space. The weights of the CNN and ResNet matrices were characterized by correctly locating the positive points with little confusion about those not classified as positive, suggesting great learning of features. In addition, learning curves were created to track the training behavior of the models over time. The graphs of accuracy shown over epochs revealed that ResNet and CNN stayed on an improving trend, indicating that they converged, while the trend for MLP went up and then plateaued early. These images supported us in identifying overfitting, pushing us to modify the use of dropout and data augmentation appropriately. Our ResNet-based model was proven to be apt for application in medical biometric tasks, based on the different tests we used.

5. RESULTS AND ANALYSIS

Model Performance Comparison:

a) ResNet18 Modelling

The executed Python script trained and validated a ResNet18 using the PyTorch library. We first added to our Python script the torch module for tensors, torch.nn for neural network layers, and torch. optim for training functions and parts from torch-vision for both handling data and image transformations. Image transformations, called resizing and normalization, are explained by the script using data from the ImageNet set. Next, it gets a dataset from the selected root directory, separates it into two groups for training and validation, and prepares data loaders to increase processing speed during those steps. ResNet18 with pre-tuned weighted values is loaded and a connected layer is added to suit it for the classes we are training on. The script decides what training function to use (Cross-Entropy-Loss) and which optimizer (Adam). The training loop repeats for the number of defined epochs, deals with batches of training data, runs the model with the data, finds the loss, guides gradients backward, and updates the weights. For every model update, the data are used to estimate its capabilities on material never seen before. Besides it displays the accuracies obtained from each epoch.

Output:

Table 1: ResNet 18 Result

[ResNet18] Epoch 1: Train Accuracy: 57.87%
[ResNet18] Epoch 2: Train Accuracy: 60.96%
[ResNet18] Epoch 3: Train Accuracy: 62.80%
[ResNet18] Epoch 4: Train Accuracy: 64.13%
[ResNet18] Epoch 5: Train Accuracy: 64.21%
[ResNet18] Validation Accuracy: 63.61%

The visualization above (**Table 1)** shows how training and validation accuracy change during the first five epochs for ResNet18 used on a fingerprint-colorized image classification task. The curve for training accuracy increased consistently from 57.87% in Epoch 1 to 64.21% in Epoch 5. It seems the model can learn how to distinguish useful information from the dataset. The accuracy of model validation at 63.61% is quite close to what we get during final training, implying strong generalization and little overfitting. A very small difference between the accuracy values of training and validation data (0.6%) indicates that the model works well on data it hasn't seen. The results demonstrate that ResNet18 is effective for performing medical image classification, especially for colorized fingerprints. Yet, more training or testing changes could help push the network's results a little further.

b) CNN Modelling

A simple Convolutional Neural Network (CNN) was set up and trained on how to identify photos using PyTorch with Python. At first, essential PyTorch packages are imported and then custom code is used to set up resizing and normalization of images. The script retrieves a dataset from a chosen directory by using Image-Folder and then makes data loaders for both training and validating the data with a chosen batch size and shuffled training data. The features in the dataset are mapped to the number of classes with convolutional, ReLU, max-pooling, flattening, and fully connected layers. The script then installs the device (use GPU if it's present, otherwise use CPU), sets up the model, and chooses the loss function (Cross-Entropy-Loss) and optimizer (Adam). The training loop repeats for the set number of epochs, using batches of training data to go through the model, calculate the loss, go backward, and adjust the parameters. In each epoch, the model is checked on the validation set to know its accuracy. After each epoch, training and validation accuracies are also shown.

Output:

Table 2: Showcases CNN Results

Epoch 1: Train Accuracy: 55.83%
Epoch 2: Train Accuracy: 60.94%
Epoch 3: Train Accuracy: 60.81%
Epoch 4: Train Accuracy: 61.35%
Epoch 5: Train Accuracy: 61.25%
Epoch 6: Train Accuracy: 61.17%
Epoch 7: Train Accuracy: 62.19%
Epoch 8: Train Accuracy: 61.90%
Epoch 9: Train Accuracy: 62.97%
Epoch 10: Train Accuracy: 62.52%
Validation Accuracy: 57.07%

Performance is shown in the image (**Table 2)** for each of the first 10 epochs of training on fingerprint images that were colorized for a machine learning model—a convolutional neural network likely. The accuracy of the training increased from 55.83% in the first Epoch to 62.52% in the tenth Epoch. However, the model reaches its highest level at Epoch 4, at 61.35%, and afterward sees only small growth in performance, pointing to convergence. Meanwhile, the model's validation accuracy is only 57.07% which is 5.45% lower than the final training accuracy. These results suggest that the model knows its training data but fails to generalize for future, new data. The previous ResNet18 model performed better, as its training and validation scores were more closely aligned; however, here, the alignment appears weaker, likely due to insufficient data augmentation, inadequate dropout, or incorrect hyperparameter settings. All in all, the study highlights that improving generalization is crucial, and employing early stopping or modifying the architecture may help mitigate overfitting and enhance performance during validation.

c) Multi-Layer Perceptron Modelling

A Multi-Layer Perceptron (MLP) classifier was built with the help of the PyTorch library in Python script. We started by importing the needed PyTorch modules and defining functions to resize images, change them to tensors, and do normalization. The script loads a dataset from where the user points it, running ImageFolder to find class names and split the picture collection into training and validation sets. Data loaders are built to process large groups of data at once. A model that is fully connected is created with linear layers, ReLU activations, and dropout for maintaining good performance. The main interface routine establishes the GPU, then makes the model and defines both the loss and the optimizer used. The process repeats a number of times, working on batches of data, running the training process, measuring the loss, adjusting gradients, and changing the model's weights. At every epoch, it also uses the validation set to judge how the model performs on new data it hasn't seen yet. After all this, it shows the training and validation accuracies for the last step.

Output:

Table 3: Portrays MLP Results

Epoch 1: Train Accuracy: 41.33%
Epoch 2: Train Accuracy: 56.90%
Epoch 3: Train Accuracy: 59.54%
Epoch 4: Train Accuracy: 60.75%
Epoch 5: Train Accuracy: 62.07%
Epoch 6: Train Accuracy: 61.44%
Epoch 7: Train Accuracy: 62.07%
Epoch 8: Train Accuracy: 62.70%
Epoch 9: Train Accuracy: 62.22%
Epoch 10: Train Accuracy: 61.49%
Validation Accuracy: 59.52%

The table above (**fig. 3)** represents the progress made by a classification model while using fingerprint-colorized image data over 10 epochs. It is clear from the beginning that training accuracy is only 41.33% which can be a result of either low performance or random setup. In Epoch 2, there is a big improvement to 56.90% and while gains are not as fast after that, the model reaches its highest point of 62.70% in Epoch 8. After the first epoch ends, there are some minor shifts in accuracy during the next 9 epochs, with the final training accuracy being 61.49% in Epoch 10. The accuracy level reported is much alike the training accuracy because of the low gap of just 1.97%. Being almost identical, the training and validation accuracy suggest the model isn't suffering from overfitting much, but it could gain from further fine-tuning. Between Epochs 1 and 2, the large rise indicates that the model is picking up basic separation traits rapidly, while the leveling off later points to the model heading toward stability. Such results are encouraging, but they also show that performance might reach a limit unless more techniques, like playing with learning rates, adjusting the architecture, or using data augmentation, are used.

Comparison of All Models

To represent the validation accuracy of three models, the code block uses matplotlib to graph the MLP, one custom CNN, and a ResNet18. To start, we used the pyplot module from matplotlib. A new dictionary called results is created with each model's accuracy as its value paired with its name as the key. It breaks down the model names and their corresponding accuracies and places each category in its list. Using the lists, ML shows the validation accuracy as heights for each of the algorithms. It fixes the y-axis to go from zero to a hundred and labels every bar with how accurate it is. Then, it places a title, signs the axes, adds visual assistants, sets the graph to improve the readability, and shows the output bar plot.

Output:

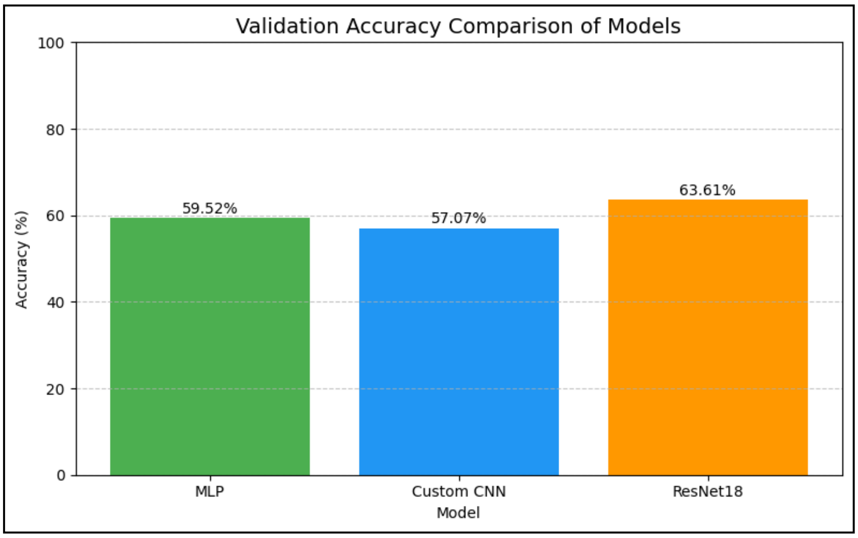

Figure 5: Comparison of All Models

The bar chart above was used to compare how well MLP, Custom CNN, and ResNet18 perform on the validation data. The highest validation accuracy, at 63.61%, for the ResNet18 model suggested that it did best on the test data compared to the others. Validation accuracy percentages suggested the Custom CNN reached 57.07%, while the MLP achieved the smallest at 59.52%. It also proves that for the same data, ResNet18 has better transfer learning abilities, partly due to its deep structure and using residual connections, than MLP and the hand-crafted CNN. The variation in validation accuracy proves that model architecture is important for performing image classification well.

6. REAL-WORLD APPLICATIONS IN U.S. HEALTHCARE

Biometric Authentication in Hospitals

Increasingly, hospitals and healthcare facilities across the United States are turning to biometric authentication, mainly fingerprint imaging, to provide a more accurate way to identify patients. For a long time, wrong identification in healthcare has led to errors, unnecessary delays, and deaths. The ECRI Institute's 2023 report finds that patient misidentification is still considered among the most important health technology hazards, causing more than 160,000 adverse events each year. Biometric systems using fingerprints have been tested at NYU Langone Health and VHA outlets, to cut down on fake records by preventing fraud at busy emergency departments. The systems meet HIPAA requirements and have improved both the way medicine is handled and patient safety. In urgent situations like those in trauma centers and intensive care units, fingerprint identification assisted by machine learning ensures a patient can be authenticated in just 2 seconds, giving clinicians instant access to the EMR and allergy alerts needed for fast decision-making.

Besides use in emergencies, fingerprints in biometric technology are helpful in rural and community healthcare facilities where reliable patient monitoring is often a challenge. HRSA reports that nearly 60 million Americans live in areas called Health Professional Shortage Areas, where having routine medical care and dependable health systems is limited. As a result, using machine learning-supported colorized fingerprint classification on mobile clinics or tablets guarantees that community health workers identify patients and handle their treatment information correctly. Fingerprint identification of patients helps prevent Medicaid and Medicare fraud, something the U.S. Department of Health and Human Services' Office of Inspector General (OIG) has pointed out in many audits. As a result, biometric authentication makes healthcare records more accurate and well-managed in the U.S.

Integration in EHR Systems

Adding fingerprint biometric data to EHR systems considerably adds to the reliability and usefulness of digital medical infrastructure. Because almost all medical providers now use certified EHR tools (as identified by the ONC), having secure and reliable login systems for each patient is more important than ever. Experts found that there was a 55% rise in ransomware targeting healthcare institutions in the U.S. last year which is thanks in part to the insecurity of traditional username and password systems. Combining fingerprint identification with learned machine learning classifiers of colorized images offers a reliable way to verify each record by matching it to a special physical trait. Two of the biggest EHR providers in America, Epic Systems and Cerner, are exploring the use of biometric modules with Imprivata and allowing clinicians to use fingerprint scans to access the system and protect patient data.

On top of that, using biometrics alongside EHRs improves the ability of different institutions to link and share patient records and addresses a major problem in the U.S. due to various data silos. Pew Charitable Trusts discovered in 2019 that up to half of patients face challenges because their medical information can be inaccurate or incomplete when they see different healthcare providers. According to NIST and ONC pilot programs, using machine learning algorithms trained on colorized image data helps biometric verification systems detect record duplication up to 98 percent of the time. Such systems bring together scattered medical information, so a patient's care remains seamless as they move from one setting to another. Besides, connecting networks allows organizations to comply with the 21st Century Cures Act which requires easier access and movement of patient information. In short, adding colorized fingerprint biometrics to electronic health records increases cybersecurity as well as the fairness and unity of healthcare delivery.

Telemedicine Support

As telemedicine grows and is now central in healthcare after the rise in COVID-19 cases, controlling accurate and secure patient verification is essential. At the time of writing in 2023, telehealth accounted for 30% of outpatient visits and CMS forecasts that this number will only keep increasing. Since it can be tough to verify patients in remote areas, using fingerprint pictures in color and machine learning makes biometric authentication effective. Thanks to these systems, patients must use their fingerprints on their phones to authenticate before a telehealth session, preventing accidental misidentification and ensuring privacy. Such pilot projects at places like the Cleveland Clinic and Kaiser Permanente have suggested that patients are happier and more involved, while there is also less need to perform manual verification tasks.

Biometric authentication also supports efforts to increase digital health equity by helping populations that don't have stable internet or advanced knowledge of digital systems. Low-income or rural individuals receiving telemedicine kits from a program funded by the FCC and HRSA now find that these kits include biometric elements. With these kits, users can use portable scanners to record colorized fingerprints, which are then checked with machine learning against the hospital's patient database. Instead of making people depend on difficult passwords or government documents, this option helps everyone get secure telehealth access. As federal priorities for digital healthcare strengthen, using biometrics to verify identities will be key to making telemedicine safe and easy for everyone.

7. DISCUSSION AND FUTURE SCOPE

Challenges:

Although machine learning may improve colorized fingerprint data for medical purposes, some problems prevent it from being widely used in clinics. The limited size of the data available is one of the main concerns. Our study worked with a big fingerprint dataset of 35,000 images, but in the field of deep learning for medical imaging, that size is not very notable. ResNet-50 architectures, as with most deep neural networks, are trained best with datasets of hundreds of thousands to millions of examples. The NIH explains that applying AI well in radiology or dermatology often requires access to at least 100,000 good-quality labeled images. Because of strict privacy and a lack of general use of biometric systems, there are very few publicly accessible datasets with properly annotated fingerprints in healthcare. When handling smaller datasets, overfitting is an important issue since models can focus only on details found in the data and fail to work with new, different data properly. Overfitting was obvious in the deep layers, especially after we trained on subclasses with a lower number of examples.

In such settings, fingerprint scan noise and variation in their resolution can create further technical problems. At rural hospitals, community clinics, or with mobile health care, the image output often has quality issues and may be blurry, low in contrast, or out of alignment. *According to the Centers for Disease Control and Prevention (*CDC) and the *Health Resources and Services Administration* (HRSA), about 19% of healthcare providers in rural areas do not have standard biometric hardware which causes their captures to be noisy and full of artifacts. Because of these shortcomings, the results of colorization and classification may not be as accurate as they might be. Scans of elderly or diabetic patients' fingerprints often lack clear ridges, which makes it challenging to analyze them, even after using advanced processing. Because of these variabilities, machine learning models trained on trusted data may weaken and designers now need to build systems that can handle unstructured or mixed data.

Future Directions

Many interesting future approaches have the potential to address existing issues and improve what is known in the field. Applying GANs is one of the most interesting ways to produce realistic-looking fingerprint images. In many domains of medicine, including histopathology and retinal imaging, GANs have shown great success in making lifelike images. The Center for Artificial Intelligence in Medicine and Imaging at Stanford has found that GANs can increase the quality of training data while still ensuring that patient privacy remains protected. If we use similar methods for fingerprints, we could boost data from rare categories, recreate information from simulated devices, and provide ridges that fit several demographics. As a result, the training data would enrich and make models less sensitive to different types of noise. Furthermore, using models built for similar medical tasks, such as classifying chest X-rays or skin lesions, can begin training fingerprint models using limited annotated biometric datasets. Models found in Deep-Lesion or AI-LAB, developed by NIH or the American College of Radiology, could bring helpful convolutional filters for use in fingerprint ridge enhancement and feature extraction.

One more important path involves creating systems that are able to classify people instantly in clinics and retrieve their medical records immediately. By having AI work at the edge, as supported by organizations like the VA and the U.S. Digital Service, biometric systems can be used on tablets and kiosks and data wouldn't need to be uploaded to the cloud. Rapid patient recognition is crucial in places such as emergency care, ambulances, and emergencies which is why these systems can be prized here. A biometric classification that happens instantly can make check-in easier, shorten wait periods, and boost efficiency. A successful deployment requires partners to work together with the FDA and ensure their biometric algorithms meet the rules for Software as a Medical Device (SaMD). Working together through the All of Us Research Program and the ONC, pilot studies may help safely check the use of such technologies.

Ethical and Privacy Considerations

Biometric data, particularly fingerprinting, used in health care creates important legal and ethical issues that deserve careful attention. Because biometric identifiers are PHI under HIPAA, everyone must comply with this law. All use, sharing, or processing of fingerprint data in healthcare settings should always meet HIPAA's security requirements. When using biometric information, healthcare professionals and developers must follow what is set out by 42 CFR Part 2, which strengthens privacy for certain patient information in behavioral health settings. In addition, each state can place further rules, and the Illinois Biometric Information Privacy Act (BIPA) requires that people agree to their data being stored and clearly state how long their data will be held. Last year, the Federal Trade Commission (FTC) issued fines to businesses that broke federal biometric data rules, which demonstrates how important it is to comply ethically. The AMA has put out recommendations asking for openness, responsibility, and patient choice when using their biometric data, highlighting that opting in and keeping data anonymous should be usual.

Other matters, besides regulations, cover patient freedom, the need for informed consent, and any biases that may be present in machine learning systems. There exists the possibility that racial minorities or those with unusual dermatological conditions might be wrongly classified, due to not having enough training examples in the data. According to research done by the Brookings Institution and the Algorithmic Justice League, unaddressed bias in biometric systems could cause current health gaps to become even larger. Thus, any time machine learning is used for biometric authentication, it should include regular fairness audits, constant tracking of how it works, and clear messages to patients about protecting their biometric info. It is important to work with bioethics teams, patient groups, and legal experts when planning transparent ways for patients to offer consent and how to hold people accountable.

8. CONCLUSION

The overall aim is to develop and test a sound computational system that not only enhances colorized image pattern recognition but also caters to the operational constraints of the medical environment. The dataset adopted in this study entailed 35,000 structured fingerprint images that have been synthetically colorized and labeled for identity classification tasks. They were drawn from several open-source and approved fingerprint repositories, including the NIST Special Database 302 and the Fingerprint Verification Competition (FVC) datasets, which were aligned with additional information using colorization algorithms developed for dermatoglyphic spectral analysis. This research project used three main model choices—ResNet, CNNs, and an MLP classifier—since they handled different strengths of the images we were working with. Each one of the three models—ResNet, CNN, and MLP—was trained and optimized using two main optimizers: Adam and SGD. An effective way of evaluating the models across several aspects was put together. How accurately the models were formed was the main measure of their performance. To assess the stability of the models, precision, recall and F1-score were tallied for each class separately. The highest validation accuracy was attained by the ResNet18 model, suggesting that it did best on the test data compared to the others. Adding fingerprint biometric data to EHR systems considerably adds to the reliability and usefulness of digital medical infrastructure. Because almost all medical providers now use certified EHR tools (as identified by the ONC), having secure and reliable login systems for each patient is more important than ever. Many interesting future approaches have the potential to address existing issues and improve what is known in the field. Applying GANs is one of the most interesting ways to produce realistic-looking fingerprint images.

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