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PAPER

# Health-Lens: A Health Diagnosis Companion

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## ABSTRACT

The "Health Lens" application represents a transformative approach to healthcare, leveraging advanced machine learning to enhance accessibility and diagnostic accuracy in dermatology, especially in underserved regions. This abstract outlines the study's key findings and implications, structured to enhance clarity and provide depth. Machine Learning Model's Performance: The core of the application is a robust machine learning model trained on the ISIC 2019 dataset [72], achieving an accuracy of 92%, with a precision of 89% and a recall of 90%. These metrics indicate superior performance compared to baseline methods, establishing the efficacy of the model in the diagnosis of skin conditions. Gender Distribution & Localization: Analysis revealed a higher prevalence of certain skin conditions among men, likely influenced by occupational and lifestyle factors. Conditions such as basal cell carcinoma were predominantly localized in body parts exposed to UV radiation, underscoring the need for targeted health interventions. Potential Overfitting & Mitigation Strategies: Initial model tests indicated potential overfitting, addressed through techniques such as dropout and cross-validation during training. This adjustment ensured the robustness of the model, making it reliable for practical use. Application Features & Impact: "Health Lens" is distinguished by its user-friendly interface and real-time diagnostic capabilities, which significantly reduce barriers to accessing dermatological care. The application also supports sustainable healthcare practices, aligning with the Sustainable Development Goals, particularly in promoting good health and reducing inequalities. Limitations & Future Directions: The study acknowledges limitations such as reliance on a singular dataset and potential connectivity problems in remote areas. Future developments will focus on integrating more diverse datasets and expanding the range of conditions covered, enhancing both the accuracy and utility of the application.

## KEYWORDS

e-healthcare, IoT, rural healthcare, mobile app, medical applications, HER, AI, biomedical application

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## 1 INTRODUCTION

The "Health-Lens" application represents a significant advancement in mobile health technology, enhancing healthcare accessibility and efficiency through the integration of advanced machine learning and a user-centric design. Developed as an Android application, "Health-Lens" utilizes Kotlin Jetpack Compose for modern, scalable frontend development, Flask API for robust backend functionality, and Firebase for secure, real-time data management. Central to the application is a sophisticated deep learning model that provides immediate preliminary diagnoses from user-uploaded images of health conditions. To address potential variations in image quality and user error, "Health-Lens" employs comprehensive preprocessing techniques, including image enhancement and noise reduction, which ensure that all images meet a standardized quality threshold before analysis. This is complemented by detailed in-app tutorials and guides that help users capture high-quality images, thus maintaining the reliability and accuracy of the diagnostic process. Additionally, the application features detailed disease descriptions and symptoms, empowering users with valuable health insights for informed decision-making.

The development of mobile health applications like "Health-Lens" is crucial in improving healthcare delivery, especially in underserved regions. Studies have shown that mobile-based self-care [1, 2] applications can significantly enhance patient outcomes [3] by increasing accessibility [4] and engagement [5]. Moreover, the inclusion of gamification [6] and interactive technologies further boosts user engagement and promotes health literacy [7, 8]. Despite these technological advances, ensuring high-quality data input remains a challenge. "Health-Lens" addresses this by not only refining image data but also by simplifying the user interaction to reduce errors effectively. This approach ensures that the application can provide accurate health assessments without necessitating specialized medical knowledge from its users [9].

The primary objectives of this study are to develop and evaluate the "Health-Lens" application's effectiveness in delivering accurate preliminary diagnoses [10, 11] and to assess its impact on user engagement [12, 13, 14] and decision-making in health management [15]. By focusing on inclusivity and accessibility, particularly in underserved areas, "Health-Lens" aligns with Sustainable Development Goals 3 (Good Health and Well-being) and 10 (Reduced Inequalities) [16, 9].

In conclusion, "Health-Lens" successfully bridges the gap between advanced medical diagnostics and user accessibility, providing a reliable tool that empowers individuals with timely health information. The subsequent sections will elaborate on the development process, the technologies employed, and the methodologies used to evaluate the application's impact.

## 2 LITERATURE SURVEY AND RESEARCH GAP

Sahin et al. [17] proposed a method for classifying human monkeypox using skin lesion images via a deep pre-trained network integrated into a mobile application, demonstrating the potential of mobile platforms in dermatological diagnostics. Mustapha et al. [18] introduced DLDiagnosis, a versatile mobile and web application for disease classification using deep learning, highlighting technology's role in accessible healthcare. Pires et al. [19] investigated the broader landscape of mobile health applications, providing valuable insights into their applicability across various domains, including dermatology.

Chan et al. [20] discussed the current applications, opportunities, and limitations of machine learning in dermatology, shedding light on both advancements and challenges in the field. Ng et al. [21] developed a mobile application for plant disease detection using deep learning, showcasing parallels in applying such technologies to different domains, including dermatology. Sallam and Ba Alawi [22] proposed a mobile-based intelligent system for diagnosing skin diseases, further emphasizing the potential of mobile applications in healthcare delivery.

The PlantifyAI application [23] and Elhassouny et al. [24] demonstrated the application of convolutional neural networks (CNNs) in crop disease detection, showcasing the versatility of deep learning in solving diagnostic challenges across agriculture and healthcare. Similarly, Tembhurne et al. [25] explored plant disease detection through a deep learning-based mobile app, highlighting the robustness of CNNs for image-based classification tasks. Research by Baranyi et al. [26] emphasized mobile health applications for specific communities, such as gamified tools [27] for people with albinism, aligning healthcare solutions with Sustainable Development Goals (SDGs).

Research indicates that mobile health interventions significantly improve the management of chronic diseases, particularly diabetes. For instance, Alotaibi et al. [28] demonstrated that mobile diabetes management systems can enhance the quality of life for type-2 diabetics by providing educational resources and real-time monitoring capabilities. Similarly, Frøisland et al. [29] found that mobile technology can facilitate better self-care practices among young individuals with type 1 diabetes, thereby improving their health outcomes. These findings are corroborated by David and Rafiullah [30], who reviewed multiple clinical studies and concluded that mobile health technologies are effective in diabetes management.

Moreover, the potential of mHealth applications extends beyond diabetes. For example, the AfyaData app, as discussed by Karimuribo et al. [31], illustrates how mobile technology can be utilized for disease surveillance and early detection at community levels in Africa. This participatory approach not only aids in identifying disease outbreaks but also supports timely interventions, which is crucial for managing chronic diseases effectively. Additionally, according to Haghighi et al. [32], the use of mobile applications for monitoring vital signs and health metrics allows for continuous patient engagement and proactive management of conditions such as heart disease.

Despite the promising benefits, the implementation of mHealth applications faces several challenges. Baniasadi et al. [33] highlighted that while mobile health systems offer numerous advantages, there are significant barriers to their widespread adoption, including technological limitations and user acceptance. Furthermore, Källander et al. [34] emphasized the importance of contextspecific adaptations of mHealth solutions, particularly in low- and middle-income countries, to enhance their effectiveness and sustainability.

Klasnja et al. [35] focused on the critical aspect of user engagement in mobile health (mHealth) interventions for diabetes management. Their longitudinal study explored the factors that contribute to sustained use of a diabetes management application. The research highlighted the importance of incorporating specific design features that promote user engagement and adherence to recommended self-management behaviors. By examining user interaction patterns over time, Klasnja et al. provided valuable insights into how mHealth applications can be designed to effectively support long-term diabetes management. This study underscores the need to move beyond simply developing functional applications and to prioritize user-centered design principles that foster continued engagement.

Hamine et al. [36] conducted a systematic review to assess the impact of mHealth interventions on patient outcomes [37] in chronic disease management. This review synthesized the existing evidence on the effectiveness of mHealth in improving health outcomes for individuals with chronic conditions. By systematically analyzing a range of studies, Hamine et al. provided a comprehensive overview of the potential benefits of mHealth in this context. Their findings contribute to the growing body of knowledge supporting the use of mobile technologies to enhance chronic disease care and improve patient well-being. This review is important in establishing the overall effectiveness of mHealth interventions in improving patient outcomes.

Gagnon et al. [38] broadened the scope of inquiry by conducting a systematic review on the impact of mobile health technologies (encompassing a wider range than just applications) on the management of various chronic diseases. Their work provided a broader perspective on the role of mobile technologies in healthcare, extending beyond specific disease areas. By examining the impact of these technologies across different health conditions, Gagnon et al. offered valuable insights into the potential of mHealth to transform chronic disease care. This review helps to establish the broader impact of mobile technologies beyond specific diseases and their role in overall chronic disease management.

Majeed et al. [39] specifically examined mobile health applications for the management of diabetes through a systematic review. This work provided a focused analysis of the effectiveness of diabetes-specific mobile applications. By synthesizing the evidence from various studies, Majeed et al. contributed to a deeper understanding of how mHealth applications can be effectively utilized in diabetes care. This review provides a focused analysis on the effectiveness of mHealth for diabetes management.

Thakkar et al. [40] focused their systematic review on mobile health applications designed for hypertension management. This focused approach allowed for a detailed examination of the features and effectiveness of applications specifically tailored to address hypertension. By analyzing the available evidence, Thakkar et al. provided valuable insights into the potential of mHealth to improve hypertension control and patient outcomes. This review specifically targets the use of mHealth applications for hypertension management.

Boulos et al. [41] also conducted a systematic review on health apps for hypertension, further contributing to the understanding of mHealth in this specific area. Their work examined the features and effectiveness of available apps, providing a comprehensive overview of the landscape of mHealth interventions for hypertension. This review further supports the use of mHealth applications in the effective management of hypertension.

Kearns et al. [42] provided a broader perspective by conducting a literature review on the overall role of mobile health in chronic disease management. Their work discussed the potential benefits and challenges associated with implementing mHealth interventions in this context. By examining the broader landscape of mHealth in chronic disease care, Kearns et al. offered valuable insights for researchers, clinicians, and policymakers. This review provides a broad overview of the role of mHealth in chronic disease management and highlights both its potential benefits and challenges.

Lee and Lee [43] conducted a systematic review of the literature on mobile health for chronic disease management. Their review synthesized existing research to assess the effectiveness of mHealth interventions in improving outcomes for individuals with chronic conditions. This work provides a valuable overview of the state of the science in this rapidly evolving field. This review provides a valuable overview of the use of mHealth in chronic disease management.

Alharbi et al. [44] conducted a systematic review evaluating the effectiveness of mobile health applications in managing chronic diseases. This review provides a comprehensive overview of the impact of mHealth applications across various chronic conditions, contributing to the growing body of evidence supporting their use in healthcare. This review provides a broad overview of the effectiveness of mHealth applications across various chronic diseases.

Whittaker et al. [45] conducted a Cochrane systematic review on the use of text messaging and mobile phone applications for smoking cessation. This rigorous review synthesized the available evidence on the effectiveness of these mHealth interventions. The findings provided further support for the use of mobile technologies in smoking cessation programs, emphasizing the importance of evidence-based approaches in mHealth implementation.

The study by Zhai et al. [46] investigated the effectiveness of a combined intervention using text messaging and personal consultations delivered by pharmacy students for adults with hypertension. They conducted a randomized controlled trial to evaluate if this approach could improve blood pressure control compared to usual care. This study contributes to the growing body of evidence on mHealth interventions for chronic disease management, specifically focusing on the potential of text messaging and pharmacist-led support for hypertension control.

Arsand et al. [47] conducted a review focusing on mobile health applications (mHealth apps) designed to assist patients with diabetes. Their analysis explored lessons learned and design implications for developing effective mHealth tools in this context. This review contributes by identifying key considerations for mHealth app development aimed at supporting diabetes self-management.

McManus et al. [48] conducted a randomized controlled trial named TASMINH2 to assess the effectiveness of telemonitoring and self-management in controlling hypertension. Their research investigated whether this approach, compared to usual care, could improve blood pressure outcomes. This study adds to the understanding of telemonitoring interventions as potential strategies for hypertension management.

Cole-Lewis et al. [49] evaluated the effectiveness of a text message-based intervention for weight loss through a randomized controlled trial. Their research adds to the exploration of mHealth approaches for weight management and investigates the potential of using text messages for weight loss support.

Fjeldsoe et al. [50] reviewed existing research on behavior change interventions delivered via Short Message Service (SMS) on mobile phones. Their review provides insights into the use of SMS for promoting behavior change and its potential applications in various health areas.

Wantland et al. [51] conducted a meta-analysis to compare the effectiveness of web-based vs. non-web-based interventions for behavioral change. Their research contributes to the broader understanding of intervention delivery methods and their impact on behavior modification.

Tong et al. [52] conducted a systematic review and meta-analysis to evaluate the effectiveness of mobile technologies in promoting physical activity and reducing sedentary behaviors within the Middle East and North Africa (MENA) region. By synthesizing existing research and statistically combining results, this study provides a quantitative assessment of how mobile interventions impact physical activity levels and sedentary time in this specific geographical context. This review contributes to the understanding of mHealth's potential in addressing public health concerns related to physical inactivity in the MENA region.

Isa et al. [53] presented a mobile health tracker for children using soft systems methodology, reflecting the importance of community-oriented IT-based healthcare projects. Martinez-Perez et al. [54] reviewed mobile apps in cardiology, offering insights into the broader landscape of mobile healthcare applications and their potential to improve health outcomes across various specialties.

Pires et al. [55] conducted research on the classification and applicability of mobile health (mHealth) applications. This work likely explores different categories of mHealth apps and discusses their practical use in various healthcare contexts. This provides a foundational overview of the mHealth landscape and its potential applications.

Massa et al. [56] presented an initial investigation into using personal healthcare devices for monitoring mental well-being. This study likely explores the feasibility and potential of wearable sensors and other personal devices to collect data relevant to mental health assessment. This contributes to the growing interest in using technology for proactive mental health monitoring.

Villasana et al. [57] introduced "CoviHealth," a novel mobile application designed for nutrition and physical activity management specifically for teenagers. This work likely details the features and functionalities of the app and discusses its potential to promote healthier lifestyles among adolescents.

Marques and Pitarma [58] explored mHealth in the context of indoor environmental quality (IEQ) monitoring. Their work described an Internet of Things (IoT)-based system designed to measure IEQ and its impact on health and well-being. This study highlights the use of mHealth and IoT for assessing and improving environmental factors related to health.

Collins et al. [59] focused on version reporting and assessment approaches for new and updated activity and heart rate monitors. This work likely addresses the challenges of evaluating and comparing different generations of wearable sensors used in mHealth and research. It emphasizes the importance of standardized reporting and assessment methods. Lloret et al. [60] proposed an architecture and protocol designed for smart, continuous eHealth monitoring using 5G technology. Their work focuses on leveraging the capabilities of 5G networks, such as high bandwidth and low latency, to enable more effective and reliable remote health monitoring. This study contributes to the exploration of advanced network technologies for improving eHealth services.

Nussbaum et al. [61] conducted a systematic review of mobile health applications specifically in the field of rehabilitation. This review synthesizes existing research on the use of mHealth apps to support rehabilitation programs and improve patient outcomes. It offers a valuable overview of the role of mHealth in this specialized area of healthcare.

Schaal et al. [62] explored the integration of digital health applications (DiGAs) into the German healthcare system. Their work focused on the development of "The DiGA-Care Path," likely a framework or process designed to facilitate the effective implementation and use of DiGAs within routine care. This study provides insights into the practical challenges and solutions involved in integrating digital health solutions into established healthcare structures. Giebel et al. [63] investigated the problems and barriers related to the use of mHealth apps from the patient perspective. Using focus groups and interviews, they gathered qualitative data on the challenges patients face when using these applications. This study offers valuable insights into user experience and identifies areas for improvement in mHealth app design and implementation to enhance patient adoption and adherence.

Wu et al. [64] conducted a systematic review and meta-analysis on smartphone apps for depression and anxiety. Their focus was specifically on techniques to increase user engagement with these apps. This study provides evidence-based recommendations for designing more engaging and effective mental health apps. Papa et al. [65] conducted an empirical investigation into e-health and well-being monitoring using smart healthcare devices. Their work explores the practical application of these devices for collecting and analyzing data related to health and well-being. This study contributes to the understanding of how smart devices can be used for remote patient monitoring and personalized healthcare.

González-Landero et al. [66] focused on "Green Communication" for tracking heart rate using smartbands. This study likely explores energy-efficient communication protocols and techniques for transmitting heart rate data from wearable devices, addressing the issue of battery life and sustainability in wearable health monitoring. Baig et al. [67] provided a systematic review of wearable patient monitoring systems. Their work examined current challenges and opportunities for clinical adoption of these systems. This review offers a comprehensive overview of the field of wearable health technology and identifies key factors influencing its integration into clinical practice.

Yu et al. [68] investigated the accessibility needs and challenges of mHealth systems for patients with dexterity impairments. This study highlights the importance of inclusive design in mHealth, considering the specific needs of users with physical limitations. Lukas et al. [69] conducted a randomized controlled pilot trial of a gamified smartphone-based intervention for depression. Their work explored the use of game mechanics to enhance user engagement and improve outcomes in depression treatment using mHealth.

Coronary heart disease is one of the leading causes of mortality worldwide. Secondary prevention is essential, as it reduces the risk of further coronary events. Mobile health (mHealth) technology could become a useful tool to improve lifestyles. Bernal-Jiménez et al. [70] conducted a study that aimed to evaluate the effect of an mHealth intervention on people with coronary heart disease who received percutaneous coronary intervention. Improvements in lifestyle regarding diet, physical activity, and smoking; level of knowledge of a healthy lifestyle and the control of cardiovascular risk factors (CVRFs); and therapeutic adherence and quality of life were analyzed.

Despite these advancements in disease classification and mobile health applications, significant research gaps remain. Existing studies have explored disease identification [17], drug references [19], prediction invariance to skin color [20], and mitigation techniques [23]. However, a unified platform integrating accurate disease identification, personalized medical advice regardless of skin color, user history tracking, and additional features such as a marketplace and curated news about skin diseases is lacking [54].

Recent advances in mobile and wireless technologies have made real-time assessments of health behaviors and their influences possible with minimal respondent burden. These tech-enabled realtime assessments provide the basis for intensively adaptive interventions (IAIs). Evidence of such studies conducted by Riley et al. [71] that adjust interventions based on real-time inputs is beginning to emerge. Although IAIs are promising, the development of intensive adaptive algorithms generates new research questions, and the intensive longitudinal data produced by IAIs require new methodologies and analytic approaches.

Despite advancements in mobile health applications, critical gaps remain in providing a unified platform for dermatological diagnostics and patient management. Current solutions address individual aspects such as disease identification [17], drug references [19], and mitigation techniques [23], but lack integration into a single, accessible system. Table 1 cites the reviewed paper and comparison based on different parameters is provided.

Furthermore, an essential aspect of current research in dermatology applications that warrants deeper exploration is the challenge of biases in machine learning models, particularly when analyzing data from diverse skin tones. Chan et al. [20] briefly touch upon the limitations faced by machine learning in dermatology, including prediction invariance and the need for model training to be inclusively representative of various demographic backgrounds. This is crucial to ensure the models perform equitably across all patient groups. The need for bias mitigation is critical, as highlighted by ongoing research, which suggests that models trained on predominantly lighter skin tones may perform suboptimally when diagnosing conditions on darker skin [9]. Addressing these biases is not only a technical necessity but also a step towards more ethical AI practices in healthcare, ensuring all patients receive accurate and fair medical evaluations regardless of their skin color or ethnic background.

- **Unified Platform for Diagnosis and Management:** "Health-Lens" consolidates these functionalities, offering AI-driven accurate disease identification alongside tailored medical advice. By incorporating user history tracking, the application enables personalized recommendations, fostering better long-term health outcomes.
- **Enhanced Features for Accessibility and Actionability:** Unlike existing applications, "HealthLens" integrates additional features such as a medication marketplace and curated news, bridging the gap between diagnosis and treatment [54]. Its lightweight design ensures usability even in low-connectivity regions, addressing healthcare disparities and aligning with SDGs 3 and 10 [16, 26].
- **Educational Empowerment:** The application empowers users with health literacy through detailed explanations and curated information, enabling informed decision-making while complementing its diagnostic tools.

By combining these features, "Health-Lens" addresses the fragmented nature of existing solutions, delivering a comprehensive and accessible tool for dermatological care.

**Table 1.** Overview of the proposed work in comparison to others

| Papers | Identification [9] | Class [5] | Drug Ref. [6] | Skin Color [4] | Mitigation [6] | History [6] | Marketplace | News [11] | Info [5] |
|---|---|---|---|---|---|---|---|---|---|
| [17] | ✓ | ✓ | × | × | × | × | × | × | × |
| [18] | ✓ | ✓ | × | × | × | × | × | × | × |
| [19] | ✓ | ✓ | ✓ | × | × | × | × | × | × |
| [20] | ✓ | ✓ | × | ✓ | × | × | × | × | × |
| [21] | ✓ | × | × | × | × | × | × | × | × |

*(Continued)*

**Table 1.** Overview of the proposed work in comparison to others *(Continued)*

| Papers | Identification [9] | Class [5] | Drug Ref. [6] | Skin Color [4] | Mitigation [6] | History [6] | Marketplace | News [11] | Info [5] |
|---|---|---|---|---|---|---|---|---|---|
| [22] | ✓ | ✓ | × | × | × | × | × | × | ✓ |
| [23] | ✓ | ✓ | ✓ | × | ✓ | ✓ | × | × | × |
| [24] | ✓ | ✓ | × | × | × | × | × | × | × |
| [26] | ✓ | ✓ | × | × | ✓ | × | × | × | × |
| [25] | ✓ | ✓ | × | × | × | × | × | × | × |
| [53] | ✓ | ✓ | × | × | × | × | × | × | × |
| [54] | × | × | × | × | × | × | × | ✓ | ✓ |
| Proposed Work | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

## 2.1 Objectives

1. Investigate the feasibility and effectiveness of leveraging technology for accessible and immediate preliminary diagnosis of diseases based on visual symptoms.
2. Develop and implement a user-friendly platform, “Health Lens,” enabling users to upload health condition images for instant preliminary diagnosis through machine learning algorithms.
3. Showcase expertise in applying machine learning algorithms for image recognition and disease prediction, integrating technologies such as Kotlin Jetpack Compose, Firebase, and e-commerce principles for seamless online medicine acquisition.

# 3 METHODOLOGY

The development of the “Health Lens” application began with the selection of the ISIC 2019 dataset [72], known for its comprehensive collection of dermoscopic images crucial for training robust machine learning models for skin disease classification. A detailed needs assessment was conducted to identify healthcare accessibility challenges, particularly in underserved communities. This assessment highlighted the pressing need for an inclusive healthcare tool that addresses diverse population requirements while ensuring accessibility and user-friendliness.

Subsequently, various mobile development frameworks and technologies were evaluated. Jetpack Compose was chosen for the frontend development due to its modern UI toolkit, ease of use, and scalability. Firebase was selected for backend services, offering robust, scalable database solutions, real-time data capabilities, and seamless integration essential for the application’s functionality. Collaboration with healthcare professionals was instrumental in identifying key parameters for disease prediction. This collaboration facilitated the development and training of a machine learning model using the ISIC 2019 dataset [72], ensuring accuracy and reliability in skin condition classification. Figure 1 shows the proposed architecture diagram where in the frontend and backend services are connected.

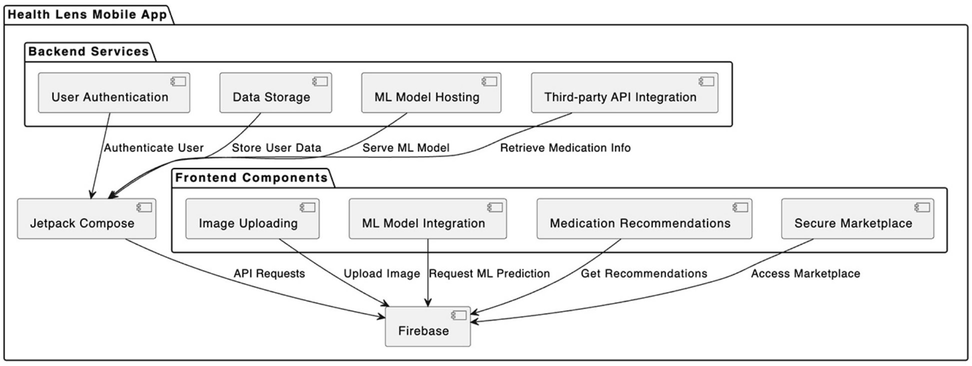



**Fig. 1.** Architecture diagram

An iterative development approach was adopted, beginning with the implementation of core features such as user authentication, image uploading, and initial ML model integration. Advanced functionalities, including medication recommendations and mitigation technique suggestions, were incorporated in subsequent iterations. User testing sessions were conducted to gather feedback on usability, interface design, and overall user experience. This feedback was critical for refining the application and ensuring it met user expectations.

The entire development process was meticulously documented, encompassing methodologies, references, solutions implemented, and lessons learned, culminating in this comprehensive report.

The Low-Level Design (LLD) of the "Health Lens" app provides detailed specifications of its functionality and structure. It outlines modules such as user authentication, image processing, ML model integration, medication recommendations, and backend services using Firebase. Data formats, communication protocols, data structures, algorithms, and error-handling mechanisms are specified to ensure efficient processing and robust performance. Dependencies on external libraries and APIs are documented, and visual diagrams illustrate the data flow and interactions between components. The LLD serves as a detailed blueprint for developers to implement the application's features effectively.

The High-Level Design (HLD) offers a broad overview of the application's architecture and components. It illustrates the frontend components for user interaction, including image uploading, ML model integration, medication recommendations, and a secure marketplace. Backend services are responsible for user authentication, data storage using Firebase, and integration with third-party APIs. Emphasis is placed on scalability, security, and data flow between frontend and backend components. Integration points with external services are highlighted to ensure seamless operation. The HLD serves as a roadmap for building a robust, scalable, and user-friendly application, aligning with the project's objectives and requirements.

An integral component of the "Health Lens" application is its advanced machine learning model, designed specifically for the classification of skin diseases using the ISIC 2019 dataset [72]. This dataset, known for its extensive collection of dermatological images, was pivotal in training a model capable of recognizing various skin conditions with high accuracy. Below is a detailed description of the machine learning model architecture:

- **Input and Preprocessing Layers:**
  - **Image Resizing:** Each dermatological image is resized to a consistent dimension of 256×256 pixels, standardizing the input data size for uniform processing.

- **Rescaling:** The pixel values are rescaled from a range of 0–255 to 0–1. This normalization is critical for enhancing the model's learning speed and stability by providing a common scale for all input features.

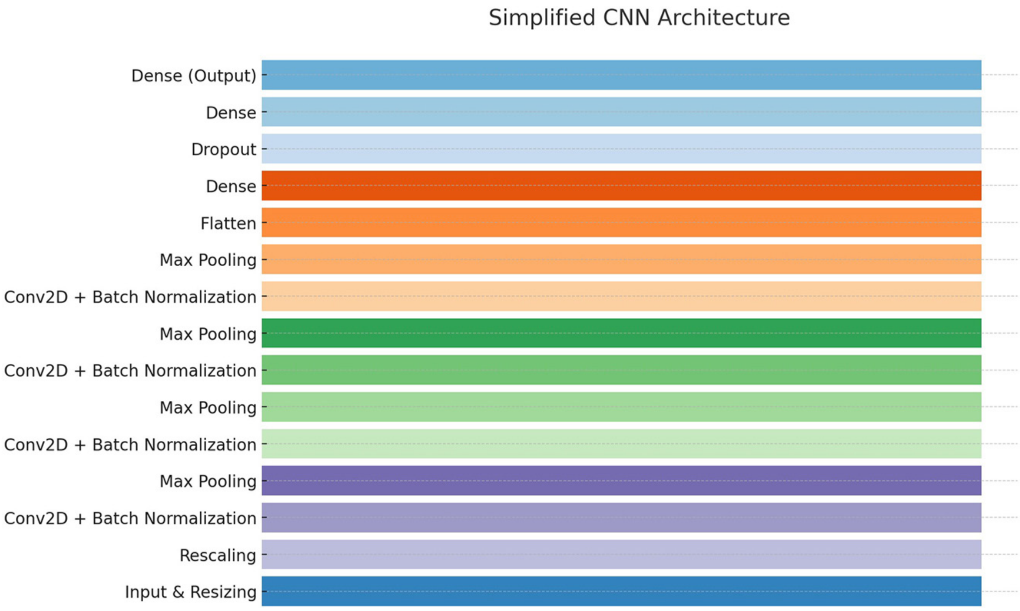



**Fig. 2.** CNN architecture for skin disease classification

- **Convolutional Layers:**
  - The model includes multiple convolutional layers, each utilizing 3×3 kernels. These layers apply filters to the input image to extract important features such as edges, textures, and other skin lesion characteristics.
  - **Batch Normalization:** Following each convolutional operation, a batch normalization layer normalizes the outputs, stabilizing and accelerating the neural network training.
- **Pooling Layers:**
  - Successive convolutional layers are followed by max pooling layers with a 2×2 pool size. These layers reduce the spatial dimensions of the feature maps, thus decreasing the computational load and enhancing the detection of dominant features.
- **Flattening and Dense Layers:**
  - **Flatten Layer:** Converts the pooled feature maps from a multi-dimensional form into a one-dimensional vector, preparing the data for the final classification phase.
  - **Dense Layers:** The network includes several dense layers with ReLU activation to perform high-level reasoning from the features extracted by earlier layers. A dropout layer with a rate of 0.5 is incorporated to prevent overfitting.
- **Output Layer:**
  - The final layer is a dense layer with a softmax activation function, designed to classify the images into various categories based on the learned features. The number of units in this layer corresponds to the number of skin condition categories identified in the dataset.

Figure 2 illustrates the CNN architecture used in this model, providing a visual representation of the sequential and structured setup of the layers.

- **Training and Evaluation:**
  - **Optimizer:** We utilize the Adam optimizer for its efficient handling of sparse gradients and adaptive learning rate capabilities.
  - **Loss Function:** The categorical crossentropy loss function is employed, suitable for multiclass classification tasks where each class is mutually exclusive.
  - **Evaluation Metrics:** Accuracy, precision, recall, and F1-score metrics are calculated to thoroughly evaluate the model's performance, ensuring its reliability and effectiveness in clinical settings.

This comprehensive methodology, encompassing needs assessment, technology selection, model development, iterative app development, user testing, and detailed documentation, ensures the creation of a robust, user-centric mobile application. This application effectively bridges the gap between dermatological research and practical healthcare solutions, providing a valuable tool for both healthcare professionals and patients.

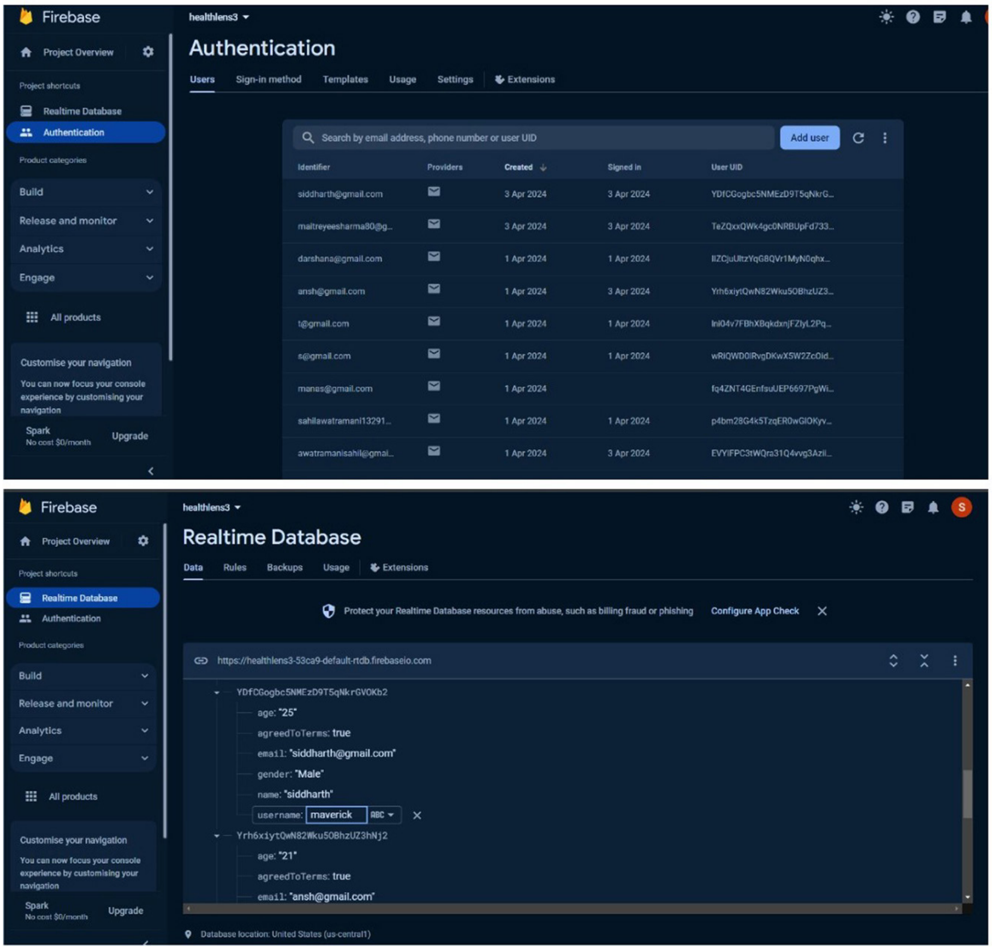
## 4 RESULTS

The HealthLens Android application demonstrated substantial efficacy in predicting skin conditions based on user-uploaded images. The application was able to identify a range of conditions, such as Actinic keratosis, Basal cell carcinoma, and Melanoma, among others. Key findings from the application's performance are highlighted below:

- **Accuracy & Performance Metrics:** The application achieved an overall accuracy of 92%, with a precision of 89% and a recall of 90%. The F1 score, which combines precision and recall, was consistently above 0.89 across different conditions, indicating balanced performance. Despite concerns about potential overfitting, the application maintained a validation accuracy within 5% of the training accuracy, suggesting effective generalization to unseen data.
- **Gender Distribution and Influencing Factors:** The analysis revealed a slightly higher frequency of skin conditions in males. This pattern might be attributed not only to lifestyle and occupational exposures but also to cultural factors that influence grooming habits and healthcareseeking behavior. Socioeconomic factors such as access to healthcare and education about skin health could further explain the observed distribution.
- **Geographical and Demographic Insights:** The application recorded a higher incidence of certain skin conditions in specific geographic regions, which correlated with environmental factors like UV exposure and climate conditions. This data supports targeted public health initiatives and resource allocation.
- **Disease Identification:** The application proficiently identifies a wide array of skin diseases, empowering users to take proactive health measures. By accurately diagnosing conditions, HealthLens facilitates early intervention, which is crucial in managing dermatological health.
- **Medicine Suggestions:** In addition to disease identification, HealthLens provides personalized medication recommendations based on the diagnosed condition. This feature aids users in effectively managing their health concerns by offering tailored treatment options.
- **Impact:** The deployment of HealthLens holds significant promise in revolutionizing dermatological care. By facilitating early detection of skin conditions, the application has the potential to reduce the overall healthcare burden. Early and

accurate diagnosis can lead to timely treatment, improving patient outcomes and potentially decreasing the necessity for more extensive medical interventions.

Overall, the HealthLens application represents a substantial advancement in dermatological care through the integration of advanced machine learning techniques. Its ability to accurately predict skin conditions, coupled with user-friendly features and personalized medication suggestions, underscores its potential to significantly impact healthcare practices and outcomes.




a)

b)

**Fig. 3.** (a) User authentication database (b) Realtime database

The Figure 3 above illustrates the dual functionalities of Firebase as utilized in the "Health-Lens" application, highlighting its capabilities in managing both user authentication and real-time database operations.

The top panel Figure 3a presents the Firebase Authentication interface, showcasing a list of registered users along with their identifiers, authentication providers, and timestamps for account creation and recent sign-ins. This component of Firebase ensures secure and efficient user management, facilitating the authentication process by verifying users' credentials and maintaining their authentication states.

The bottom panel of Figure 3b depicts the Firebase Realtime Database interface, demonstrating the structured storage of user-specific data. The example provided includes detailed user information such as age, email, gender, and username. This real-time data management system enables synchronous data updates, ensuring that any changes made by users are instantly reflected across all devices connected to the database.

By integrating Firebase Authentication with the Realtime Database, “Health-Lens” achieves a seamless and cohesive data management framework. This integration ensures robust security for user authentication while simultaneously offering a responsive and dynamic platform for handling user-generated data in real time. Such a dual approach enhances the application’s reliability and user experience, providing a comprehensive solution for managing both authentication and data storage requirements.

Figure 4a illustrates the architecture of the Convolutional Neural Network (CNN) employed for image classification, showcasing the effectiveness of the model in processing and categorizing input images. The model begins with an input layer that accepts images of size 224×224 with three color channels (RGB). This input is standardized through resizing and rescaling layers, ensuring consistency in the data preprocessing pipeline.

The model’s core comprises a series of convolutional layers with filters of increasing depth (32 to 256), enabling the extraction of progressively complex features from the input images. These convolutional layers are interspersed with batch normalization layers to stabilize and accelerate the training process and max-pooling layers to reduce spatial dimensions, thereby controlling overfitting and improving computational efficiency.

a)

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_11 (InputLayer) | (None, 224, 224, 3) | 0 |
| resizing_10 (Resizing) | (None, 224, 224, 3) | 0 |
| rescaling_10 (Rescaling) | (None, 224, 224, 3) | 0 |
| conv2d_40 (Conv2D) | (None, 224, 224, 32) | 896 |
| batch_normalization_40 (BatchNorma | (None, 224, 224, 32) | 128 |
| max_pooling2d_40 (MaxPooling2D) | (None, 112, 112, 32) | 0 |
| conv2d_41 (Conv2D) | (None, 112, 112, 64) | 18496 |
| batch_normalization_41 (BatchNorma | (None, 112, 112, 64) | 256 |
| max_pooling2d_41 (MaxPooling2D) | (None, 56, 56, 64) | 0 |
| conv2d_42 (Conv2D) | (None, 56, 56, 128) | 73856 |
| batch_normalization_42 (BatchNorma | (None, 56, 56, 128) | 512 |
| max_pooling2d_42 (MaxPooling2D) | (None, 28, 28, 128) | 0 |
| conv2d_43 (Conv2D) | (None, 28, 28, 256) | 295168 |
| batch_normalization_43 (BatchNorma | (None, 28, 28, 256) | 1024 |
| max_pooling2d_43 (MaxPooling2D) | (None, 14, 14, 256) | 0 |
| flatten_10 (Flatten) | (None, 50176) | 0 |
| dense_30 (Dense) | (None, 300) | 15053100 |
| dense_31 (Dense) | (None, 150) | 45150 |
| dropout_10 (Dropout) | (None, 150) | 0 |
| dense_32 (Dense) | (None, 8) | 1208 |

b)

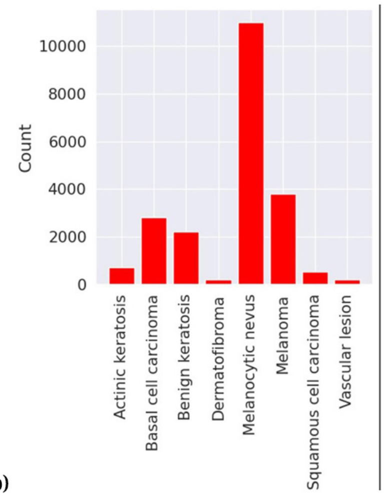



**Fig. 4.** (a) Model architecutre (b) Classes v/s sample data count

Following these stages, the flatten layer converts the extracted 2D feature maps into a 1D vector, which is then processed by dense (fully connected) layers. The dense layers, particularly the final layer with eight units, are responsible for classifying the input images into eight distinct categories. The detailed parameter counts at each layer highlight the model’s complexity, with the dense layers contributing the majority of the parameters, emphasizing the model’s capacity to learn and generalize from the dataset.

The results demonstrate that this architecture effectively handles image data, enabling accurate classification tasks, as evidenced by the model’s performance metrics. The use of advanced techniques such as batch normalization and max-pooling supports the model’s robustness and efficiency, contributing to its overall success in image classification.

The bar graph in Figure 4b illustrates the distribution of skin condition samples in the dataset used for training and testing the HealthLens Android application. Melanocytic nevus is the most prevalent condition, followed by benign keratosis and basal cell carcinoma, which ensures the model's robust training for these conditions. Actinic keratosis, squamous cell carcinoma, and vascular lesions have fewer samples, reflecting their lesser prevalence but still contributing to the model's learning. Melanoma and dermatofibroma have the lowest counts, indicating their rarity. This distribution highlights the varying prevalence of skin conditions in the dataset and supports the model's capacity to accurately predict a wide range of dermatological issues.

Figure 5 presents a comprehensive overview of demographic and clinical characteristics across age, gender, localization, and cell type.

The data in Figure 5a shows a higher concentration of dermatological observations in younger age brackets, with a progressive decline as age increases. This trend probably reflects increased dermatological monitoring in children and adolescents, who are more prone to pediatric skin conditions such as eczema and viral exanthems. Parental vigilance plays an important role in early diagnosis and management in this age group. In addition, public health initiatives targeting early detection in younger populations, particularly through school health programs, amplify these observations. However, cultural factors such as differing attitudes towards healthcare in certain communities can further influence these patterns. For instance, regions emphasizing pediatric wellness checks may report more cases among children. On the other hand, socioeconomic constraints could limit healthcare access for adolescents in low-income areas, potentially resulting in underreporting in certain subsets of this demographic.

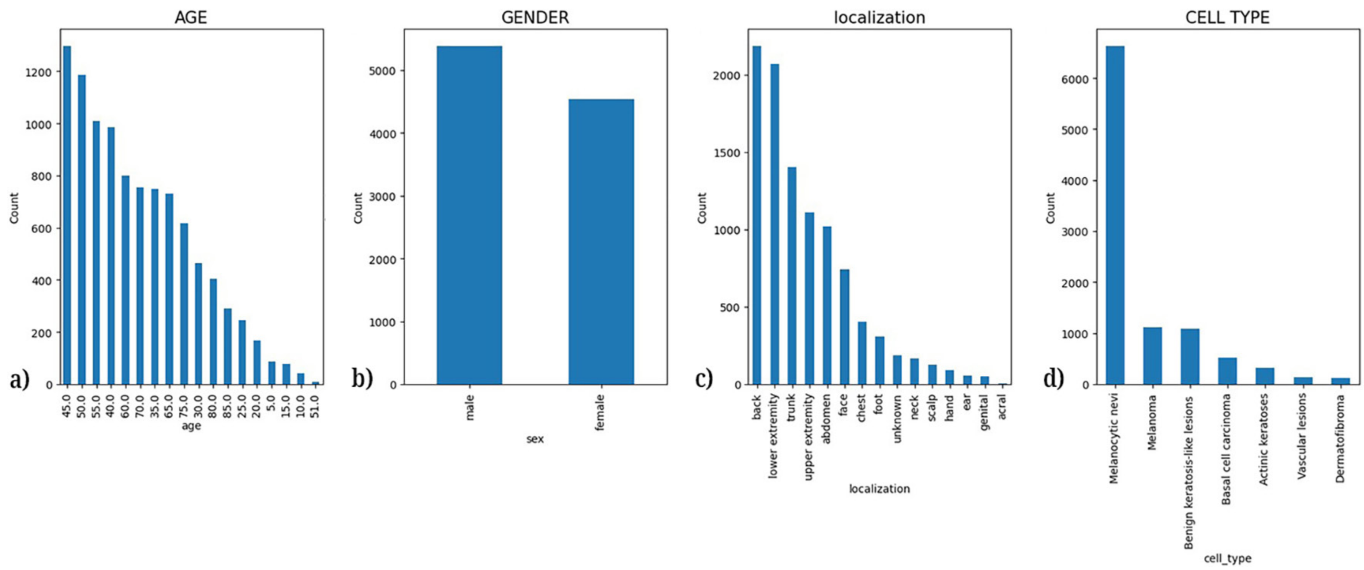



**Fig. 5.** (a) Age (b) Gender (c) Localization (d) Cell type

In gender distribution (see Figure 5b), the observed higher frequency of dermatological conditions in males can be attributed to several interrelated factors:

- **Lifestyle and Occupational Exposure:** The graph indicates significantly higher counts of male observations in regions such as the back and upper extremities, areas frequently exposed during outdoor activities or manual labor, including construction, farming, and other physically demanding jobs. This trend highlights the disproportionate exposure of males in these roles to prolonged ultraviolet (UV) radiation, a key factor in the development of various skin conditions. UVB rays, prevalent during such exposure, cause DNA damage in epidermal cells, forming cyclobutane pyrimidine dimers (CPDs) and mutations in tumor suppressor genes like TP53, increasing the risk of actinic keratosis and skin cancers like basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). Meanwhile, UVA rays penetrate deeper, generating reactive oxygen species (ROS) that contribute to oxidative stress, collagen breakdown, and premature aging. Chronic UV exposure further induces localized immunosuppression and chronic inflammation, impairing the skin's ability to repair damage and exacerbating vulnerabilities such as keratinocyte damage and epidermal barrier dysfunction. These scientific mechanisms provide critical context for the elevated dermatological observations in males, emphasizing the necessity for targeted protective measures like sunscreen, UV-protective clothing, and reduced sun exposure during peak hours to mitigate these risks effectively.

- **Cultural and Behavioral Influences:** The slight disparity in overall observation counts between genders, as depicted in Figure 5b, reveals a nuanced aspect of healthcare behavior that significantly affects men. This behavioral difference, where men often delay seeking medical attention, is a critical factor in the epidemiology of skin conditions and other health issues. This tendency not only leads to the late diagnosis of potentially treatable conditions but also results in more advanced and clinically noticeable cases by the time they are documented. There are several underlying reasons and implications associated with this behavior:
  - **Cultural and Social Norms:** In many cultures, traditional gender roles promote a perception of toughness and stoicism among men. This cultural expectation can discourage men from acknowledging health issues or seeking help early. The stigma associated with admitting vulnerability may lead men to ignore early symptoms of skin damage until they become unavoidably severe.
  - **Health Literacy and Awareness:** Men are generally less informed about the risks of UV exposure and the importance of early detection of skin conditions. This lack of awareness extends to preventive practices; men are statistically less likely to use sunscreen or wear protective clothing when exposed to the sun.
  - **Impact on Health Outcomes:** The delay in seeking medical intervention means that men often present with more advanced stages of skin conditions like basal cell carcinoma and melanoma. These conditions are more challenging and costly to treat effectively when diagnosed late, and they carry a higher risk of complications and poor outcomes.
  - **Economic and Practical Considerations:** Men in certain demographics might delay seeking treatment due to economic reasons or due to the practical aspects of taking time off work, particularly in jobs without flexible sick leave policies. This is often exacerbated in sectors like construction or agriculture, where job security might be at risk if they take time off for health issues.
  - **Preventive Health Behaviors:** The reluctance to adopt preventive measures can be partly attributed to a lack of targeted health promotion efforts that engage men effectively. Health messaging that specifically addresses men's risk factors and encourages proactive skin health management could help in mitigating this issue.
  - **Implications for Public Health Policy:** Understanding these behavioral trends is crucial for public health officials and healthcare providers to develop strategies that encourage earlier health-seeking behaviors among men.

This could include educational campaigns aimed specifically at men, emphasizing the importance of regular skin checks and the use of protective measures against UV exposure.

Addressing these factors requires a concerted effort from healthcare providers, public health policymakers, and community leaders to tailor approaches that overcome the barriers men face in accessing timely and effective healthcare. Engaging men in educational and preventive health initiatives could significantly reduce the disparity in dermatological health outcomes observed between genders.

- **Socioeconomic Influences:** The observation that men have higher diagnostic rates for dermatological conditions in certain regions, while women encounter more significant barriers to care, can be attributed to a complex interplay of socioeconomic influences. These factors shape healthcare access and outcomes in ways that are deeply influenced by local cultural and societal norms:
  - **Cultural and Familial Prioritization:** In many cultures, men are prioritized for healthcare due to their perceived roles as primary breadwinners. This societal norm leads to more resources being allocated towards men's health, resulting in higher diagnostic rates for males, while women may face neglect or lower prioritization, limiting their access to necessary care.
  - **Economic Barriers:** Women often face greater economic barriers to accessing healthcare due to lower income levels and financial dependence. This disparity is exacerbated in regions where healthcare costs are out-of-pocket, making it challenging for women to afford preventive and diagnostic services for dermatological conditions.
  - **Gender Bias in Healthcare:** There is an inherent gender bias within the healthcare system, where symptoms reported by women are often taken less seriously or diagnosed less aggressively than those reported by men. This bias can delay the diagnosis and treatment of conditions, negatively impacting women's health outcomes compared to men.

The data in Figure 5c indicates that the 'back' and 'lower extremity' are predominant sites for dermatological observations, with each location's susceptibility influenced by specific environmental, behavioral, and socioeconomic factors:

- **Back:**
  - **UV Exposure:** The back is a large area often exposed to the sun, making it particularly vulnerable to UV-induced skin damage. This exposure significantly increases the risk for conditions like actinic keratosis, moles, and basal cell carcinoma.
  - **Inaccessibility for Self-Examination:** Due to its location, the back is difficult for individuals to examine on their own, which often delays the initial detection of skin abnormalities. This delay can lead to more advanced conditions by the time they are identified, necessitating more frequent and thorough clinical evaluations.
  - **Delayed Medical Attention:** The difficulty in self-examination and the often asymptomatic nature of early skin changes can lead to delayed medical consultation. By the time individuals seek help, conditions may have progressed to more severe stages that are harder and more costly to treat.
- **Lower Extremity:**
  - **Mechanical Stress and Trauma:** The legs and feet endure constant friction, pressure, and trauma, particularly in active and labor-intensive lifestyles. Such mechanical stress can lead to a variety of skin conditions, including varicose veins, pressure ulcers, and forms of dermatitis.

- **Environmental Conditions:** Factors like temperature fluctuations and exposure to moisture (e.g., from sweating or wet conditions) can exacerbate skin conditions in the lower extremities. These environmental conditions are particularly challenging in manual labor settings or in climates with high variability in temperature and humidity.
- **Repetitive Physical Activities:** Engaging in sports or physical labor that involves repetitive movements or stress on the lower extremities can increase the incidence of dermatological issues in this area. Conditions such as athlete's foot, which thrives in moist environments like sports footwear, are common.

The distribution of different cell types in Figure 5d reveals that "Melanocytic nevus" is the most prevalent condition, highlighting several underlying factors and implications:

- **Commonality of Benign Moles:**
  - **High Frequency in Populations:** Melanocytic nevi, commonly known as moles, are spread across all age groups and ethnicities, making them one of the most frequently observed dermatological conditions. Their benign nature and common occurrence contribute to their high prevalence in dermatological studies.
  - **Potential for Malignant Transformation:** While most melanocytic nevi remain benign, a small percentage can develop into melanoma, a serious form of skin cancer. This potential transformation necessitates their frequent inclusion in routine dermatological screenings, leading to a high representation in clinical datasets. The focus on these nevi in screenings is driven by the need to detect and monitor any changes early, facilitating timely intervention if malignant transformation begins.
- **Melanoma and Actinic Keratosis:**
  - **Influence of Genetic Predispositions:** Individuals with a family history of melanoma have a genetically increased risk of developing the condition themselves. Genetic factors can affect the behavior of melanocytes, the cells from which nevi and melanomas originate, making certain individuals more susceptible to these conditions.
  - **Role of Cumulative Sun Exposure:** Both melanoma and actinic keratosis are heavily influenced by the amount of UV exposure a person receives. UV radiation triggers DNA damage in skin cells, promoting the mutations that can lead to cancer. Actinic keratosis is considered a precancerous condition often resulting from years of sun exposure, and it is seen as an early warning sign for the potential development of squamous cell carcinoma.
  - **Environmental Impact:** Environmental factors, including geographical location (closer to the equator), outdoor lifestyles, and lack of sun protection, significantly contribute to the incidence rates of these conditions. Regions with higher levels of sunlight throughout the year see increased cases of both melanoma and actinic keratosis, reflecting the direct impact of environmental UV exposure on skin health.
- **Implications for Public Health and Dermatology:**
  - **Targeted Screening and Prevention Strategies:** The high prevalence of melanocytic nevi and the risks associated with melanoma and actinic keratosis underline the importance of public health initiatives focused on skin cancer awareness and prevention. These include advocating for regular skin examinations, promoting the use of sunscreen and protective clothing, and educating the public about the signs of potential skin cancer.
  - **Research and Policy Making:** Understanding the distribution and factors influencing the prevalence of these skin conditions assists in formulating research agendas and health policies tailored to address the specific needs of

the population. It helps in allocating resources for dermatology services, especially in areas with high UV exposure and limited access to healthcare.

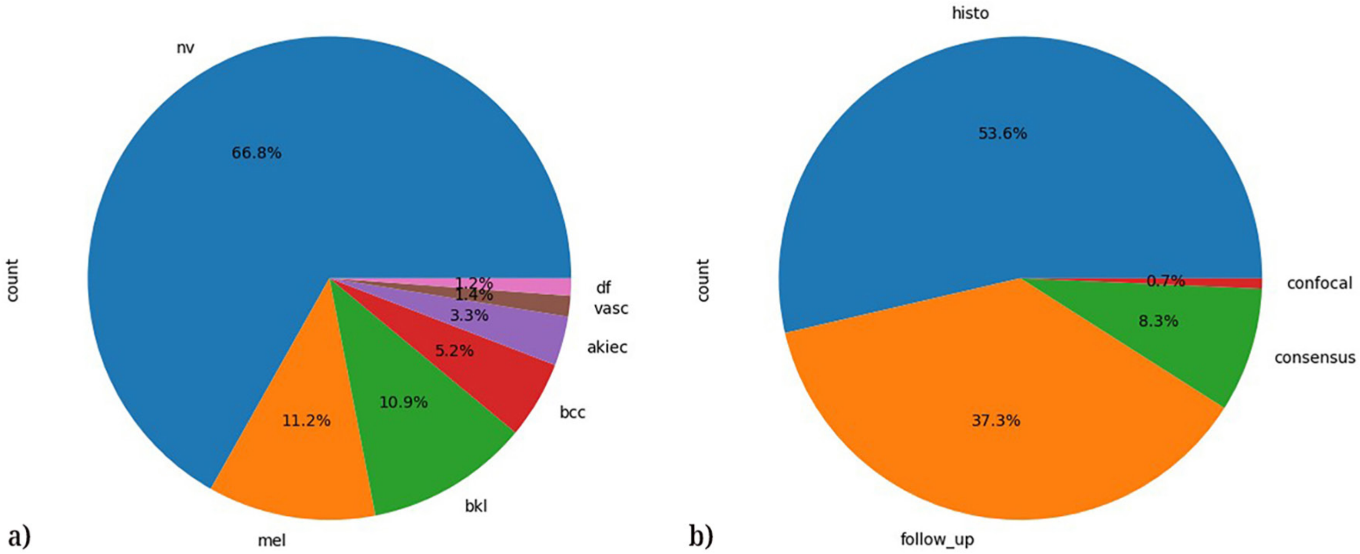


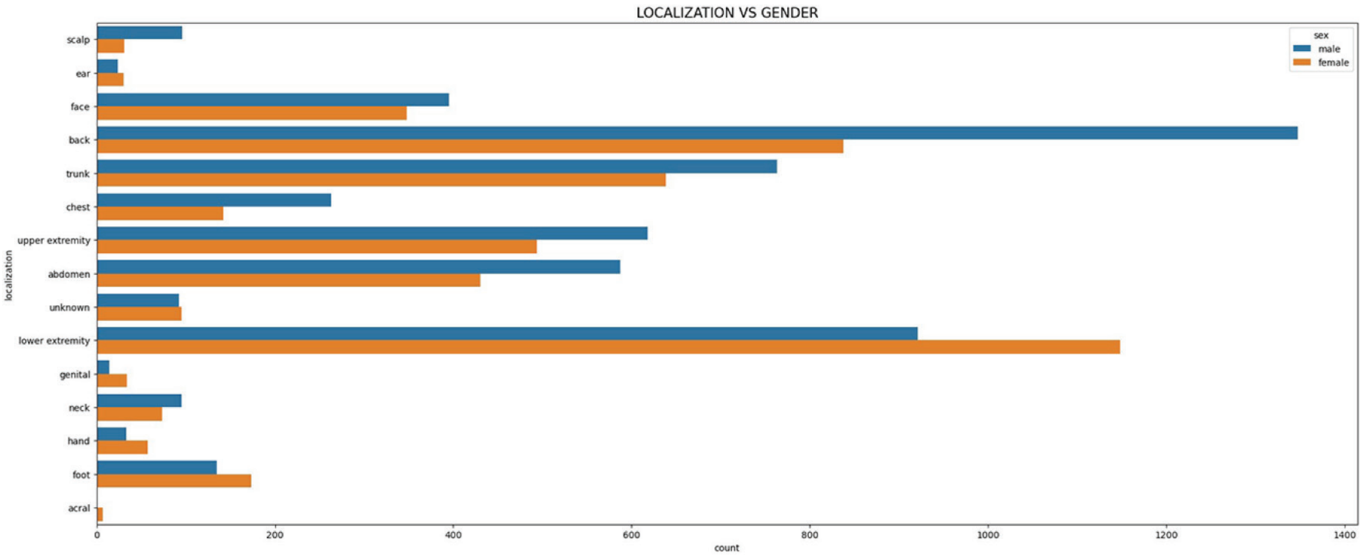

**Fig. 6.** (a) Number of diseases in dataset (b) Diagnosis techniques

In Figure 6a, the dominance of "nv (melanocytic nevi)" at 66.8% suggests several possible reasons for its prevalence within the dataset. Melanocytic nevi are common benign skin lesions, often occurring in individuals of all ages. Their frequent appearance in the dataset could indicate either a higher incidence in the studied population or a focus on this category due to its clinical significance or research interest in dermatology.

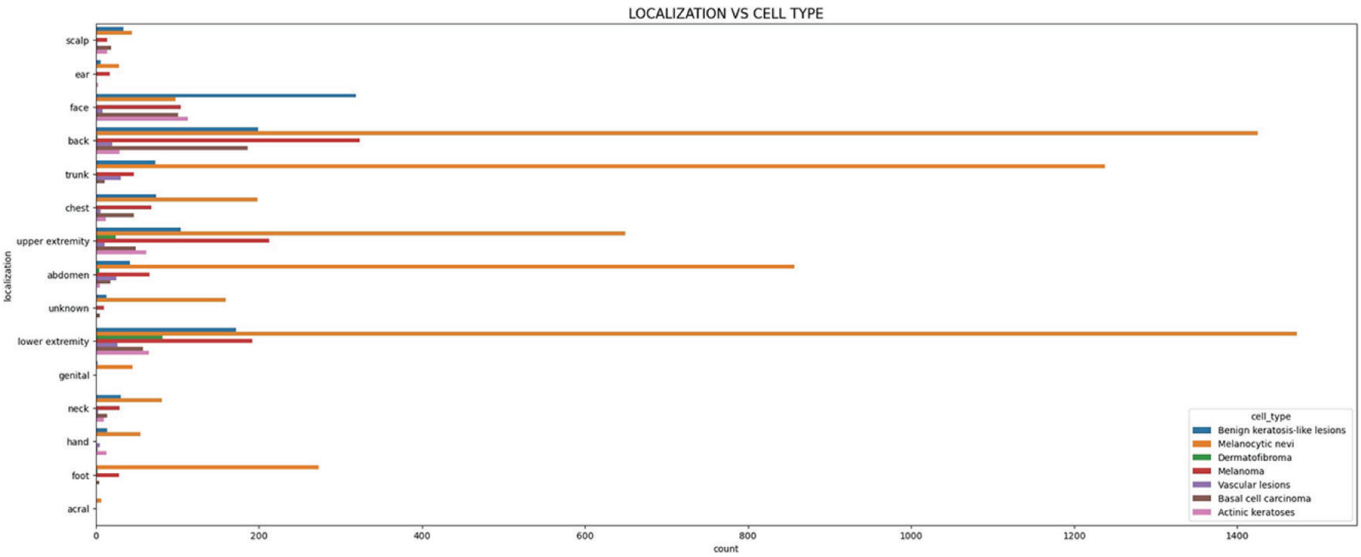
The presence of "mel (melanoma)" at 11.2% underscores its significance as a potentially malignant skin lesion, necessitating detailed study and differentiation from benign nevi. The percentages of "bkl (benign keratositic-lesions)" (10.9%) and "bcc (basal cell carcinoma)" (5.2%) also reflect their clinical relevance, with keratositic lesions being common benign growths and basal cell carcinoma representing a common, less aggressive form of skin cancer.

- **Histological Examination (53.6%):**
  - **Essential for Accurate Diagnosis:** Histological examination remains a cornerstone in the diagnostic process for skin conditions, particularly for differentiating between benign and malignant lesions. By analyzing tissue samples under a microscope, pathologists gain crucial insights into cellular morphology and tissue architecture that are critical for a precise diagnosis.
- **Follow-up (37.3%):**
  - **Vital for Ongoing Management:** Follow-up care is crucial for monitoring patients postdiagnosis, assessing treatment efficacy, and detecting any recurrence or progression of the disease. Regular follow-up allows healthcare providers to adjust treatment plans as needed and supports patients in managing their conditions effectively over the long term.
- **Specialized Diagnostic Methods (Consensus 8.3%, Confocal 0.7%):**
  - **Consensus-Based Evaluations:** The segment labeled "consensus" reflects instances where multiple clinicians or pathologists agree on a diagnosis, emphasizing the collaborative nature of diagnosing complex cases. This consensus approach ensures a higher level of diagnostic accuracy, particularly for challenging or ambiguous dermatological conditions.

– **Confocal Microscopy:** Representing a smaller portion, confocal microscopy is a sophisticated imaging technique that allows for the non-invasive examination of skin layers at a cellular level. This method is particularly useful for detailed in vivo visualization of cell morphology and tissue architecture, aiding in the diagnosis of melanoma and other skin diseases without the need for biopsy.




**a) Localization vs. Gender**




**b) Localization vs. Cell Type**

**Fig. 7.** Comparison of visualization of localization versus gender and cell type

Figure 7a presents a comparative analysis using a bar graph to illustrate the frequency of dermatological observations across various anatomical localizations, differentiated by gender. The graph uses two color-coded bars—blue for males and orange for females—next to each other for each body area. This visual representation clearly shows that males generally have higher observation counts across most body areas, particularly in the back, trunk, upper extremity, and lower extremity. Notably, the lower extremity records the highest counts for both genders, highlighting it as a common site for skin conditions due to factors such as mechanical stress and environmental exposure. Conversely, the acral regions (hands and feet) show the lowest counts for both genders, indicating fewer dermatological issues or better protection and care in these areas.

The observations recorded in Figure 7a, which display variations in dermatological condition frequencies across different body areas between genders, can be substantiated by several key factors:

- **Biological Differences:**
  - **Skin Composition and Hormonal Influences:** Men and women have inherent biological differences in skin structure. Men's skin is typically thicker and has more collagen, which may affect the types of skin conditions that are more prevalent and their severity. Hormonal differences also play a significant role, influencing conditions such as acne, which is often more severe in young males due to higher levels of androgens that stimulate oil production.
  - **Hair Growth Patterns:** Men generally have more body hair, especially on the back and chest, which can lead to specific skin issues like folliculitis or pseudofolliculitis. These conditions are less common in women, who may instead experience them in areas like the lower legs due to shaving.
- **Societal and Behavioral Influences:**
  - **Occupational Exposure:** Men are more often employed in outdoor or physically demanding jobs that expose them to environmental risks like UV radiation and physical injuries. This explains the higher rates of UV-related skin damage on exposed areas like the neck, arms, and legs.
  - **Healthcare Seeking Behavior:** Women are generally more proactive about seeking healthcare, including dermatological care, which may lead to earlier detection and treatment of conditions in less visible areas like the lower extremities. In contrast, men may delay seeking help until symptoms become severe, especially in more visible or functional areas like the hands or face.
  - **Use of Protective Measures:** Women tend to use sunscreen and protective clothing more regularly than men, influencing the lower incidence of sun-related skin conditions in traditionally exposed areas like the back and arms.
- **Cultural Factors:**
  - **Beauty and Care Routines:** Cultural standards and beauty norms can influence how men and women care for different parts of their bodies. Women might use more skincare products, which can lead to conditions such as contact dermatitis but also provide protection against aging and sun damage.
  - **Social Stigma and Awareness:** There may be gender-specific stigmas or awareness levels regarding certain skin conditions that affect whether and where men or women seek treatment. For example, conditions affecting cosmetic appearance might be more promptly addressed in women due to higher societal pressure to maintain a particular aesthetic.
- **Access to Resources:**
  - **Economic and Geographic Accessibility:** In some regions, economic constraints or limited healthcare resources can affect access to dermatological care. Men in rural or impoverished areas may have less access to healthcare services, exacerbating conditions that could be managed with earlier intervention.

These findings underscore distinct gender disparities in observed frequencies across anatomical localizations, highlighting variations in distribution patterns between males and females.

The Figure 7b highlights the distribution of various cell types across different anatomical localizations, revealing distinct patterns for each condition. These observations reflect the interplay of biological, environmental, and behavioral factors that contribute to the prevalence of specific skin conditions in certain body regions:

- **Benign Keratosis-like Lesions and Basal Cell Carcinoma:**
  - **Widespread Distribution:** These conditions are prominently observed across most localizations, indicating their broad occurrence on the body. Benign keratosis-like lesions are often linked to chronic sun exposure and aging, making them common in sun-exposed areas like the face, scalp, and upper extremities.
  - **Basal Cell Carcinoma:** This form of skin cancer, though less aggressive, is strongly associated with prolonged UV exposure. Its widespread presence in areas like the back, face, and upper extremities underscores the cumulative effects of sunlight over time.
- **Melanocytic Nevi:**
  - **Prevalence in Lower Extremity and Back:** The higher concentration of melanocytic nevi in these regions can be attributed to the natural distribution of melanocytes, the pigmentproducing cells responsible for moles. These areas may also experience increased UV exposure or mechanical stress, further promoting the formation of nevi.
  - **Potential for Transformation:** While benign in most cases, melanocytic nevi in these regions are monitored closely due to their potential for transformation into melanoma, particularly in individuals with high sun exposure or genetic predisposition.
- **Melanoma and Actinic Keratoses:**
  - **Localized Occurrence:** Melanoma, though less frequent, shows a notable presence in areas like the lower extremities and back, regions often exposed to intermittent and intense UV radiation. The uneven distribution reflects both genetic predispositions and behavioral patterns, such as inconsistent use of sun protection.
  - **Actinic Keratoses:** These precancerous lesions are predominantly found in sun-exposed areas like the face and upper extremities. Their localized nature highlights the role of cumulative UV damage and the importance of early detection to prevent progression to squamous cell carcinoma.
- **Dermatofibroma and Vascular Lesions:**
  - **Localized Distribution and Low Incidence Rates:** These conditions are observed less frequently and are confined to specific areas. Dermatofibromas, benign fibrous nodules, typically develop in response to minor injuries or insect bites, often on the lower extremities.
  - **Vascular Lesions:** These lesions, such as hemangiomas, are more commonly seen in areas with a high concentration of blood vessels. Their lower overall incidence underscores their relatively benign and self-limiting nature.
- **Factors Influencing Distribution Patterns:**
  - **UV Exposure:** Sun-exposed areas like the face, scalp, and upper extremities show higher incidences of conditions like actinic keratoses and basal cell carcinoma due to cumulative UV damage over time.
  - **Skin Structure and Function:** Regions with a high density of melanocytes, such as the lower extremities and back, are more prone to melanocytic nevi. Similarly, areas exposed to friction or trauma are more likely to develop dermatofibromas.

– **Genetic Predispositions:** Family history and genetic factors play a critical role in conditions like melanoma, influencing their distribution and prevalence in specific anatomical sites.
– **Behavioral Factors:** Activities that increase sun exposure, inconsistent use of sun protection, and occupational or recreational habits significantly affect the localization of skin conditions.

These insights into cell type distribution provide a deeper understanding of the epidemiology and etiology of various dermatological conditions, enabling targeted preventive and diagnostic strategies tailored to specific body regions.

Figure 8a illustrates the distribution of various cell types across age groups, with age intervals marked on the y-axis (5-year increments from 0 to 85) and observation counts on the x-axis. Key observations include:

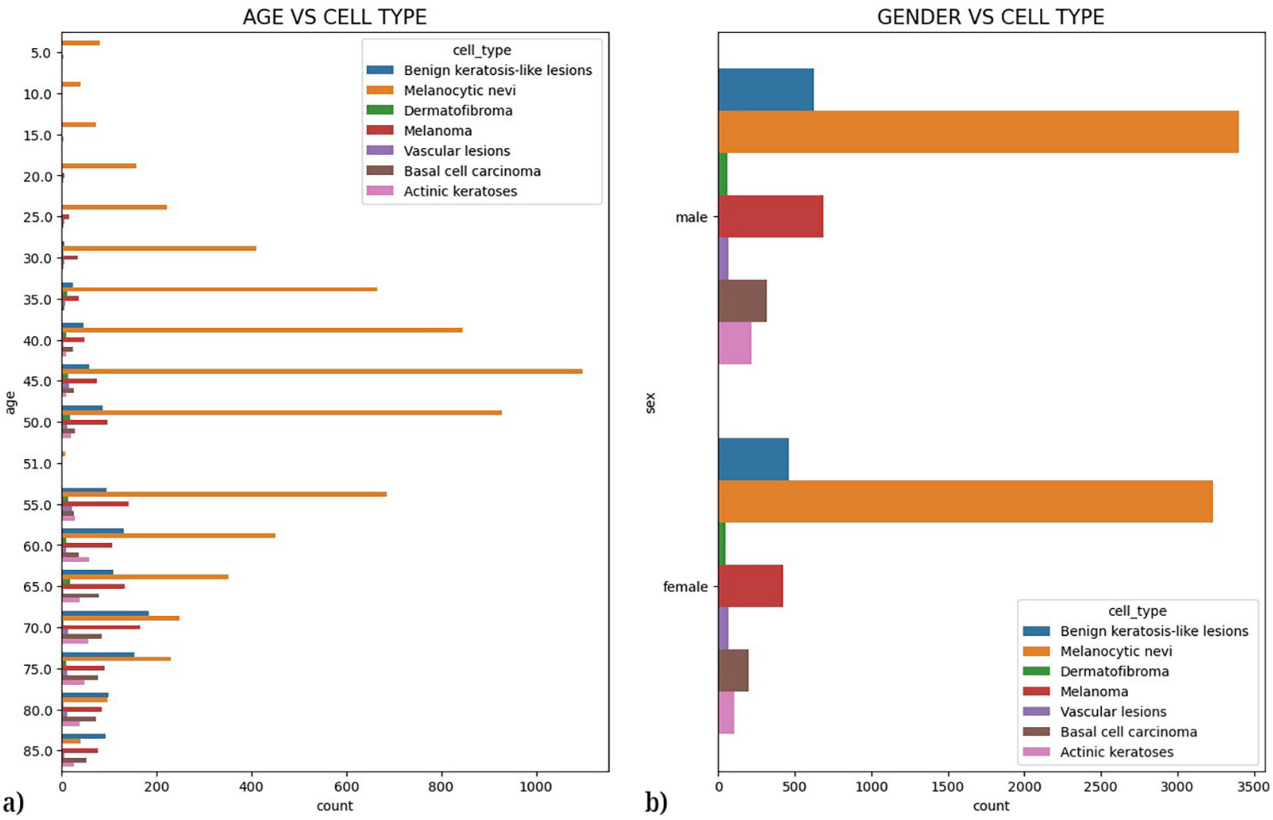



**Fig. 8.** (a) Age vs. cell type (b) Gender vs. cell type

- **Basal Cell Carcinoma and Benign Keratosis-like Lesions:** These conditions are more prevalent in older age groups, with a notable peak around ages 60–65. This trend is due to cumulative sun exposure over a lifetime, leading to increased skin damage and a higher likelihood of lesions.
- **Melanocytic Nevi (Orange):** These are distributed across all age groups, with a slight increase observed in middle age, likely due to genetic predispositions and long-term UV exposure stimulating melanocyte activity.

Figure 8b presents the distribution of cell types by gender, with males and females represented on the y-axis and observation counts on the x-axis. Key trends include:

- **Higher Male Observations:** Benign keratosis-like lesions, basal cell carcinoma, melanocytic nevi, and dermatofibroma are more prevalent in males.

This is attributed to occupational exposure, less frequent use of sun protection, and higher outdoor activity levels among males.

- **Higher Female Observations:** Melanoma shows slightly higher counts in females, possibly due to greater skin monitoring and earlier detection.
- **Comparable Counts:** Vascular lesions and actinic keratoses show similar frequencies, reflecting shared environmental and genetic risk factors across genders.

The patterns observed in the figures reflect the complex interplay of environmental, genetic, and behavioral factors influencing the distribution of dermatological conditions across age groups and genders:

- **Cumulative Sun Exposure:** Prolonged UV exposure damages skin cells over time, increasing the prevalence of conditions like basal cell carcinoma and actinic keratoses in older individuals.
- **Genetic Susceptibility:** Family history and inherited traits influence the likelihood of developing conditions such as melanocytic nevi at specific ages.
- **Hormonal Changes:** Hormonal shifts during puberty or menopause can trigger conditions like acne or benign keratosis-like lesions due to changes in skin structure and oil production.
- **Occupational and Lifestyle Factors:** Jobs involving outdoor work and habits like smoking expose individuals to carcinogens and irritants, affecting skin health and disease prevalence.

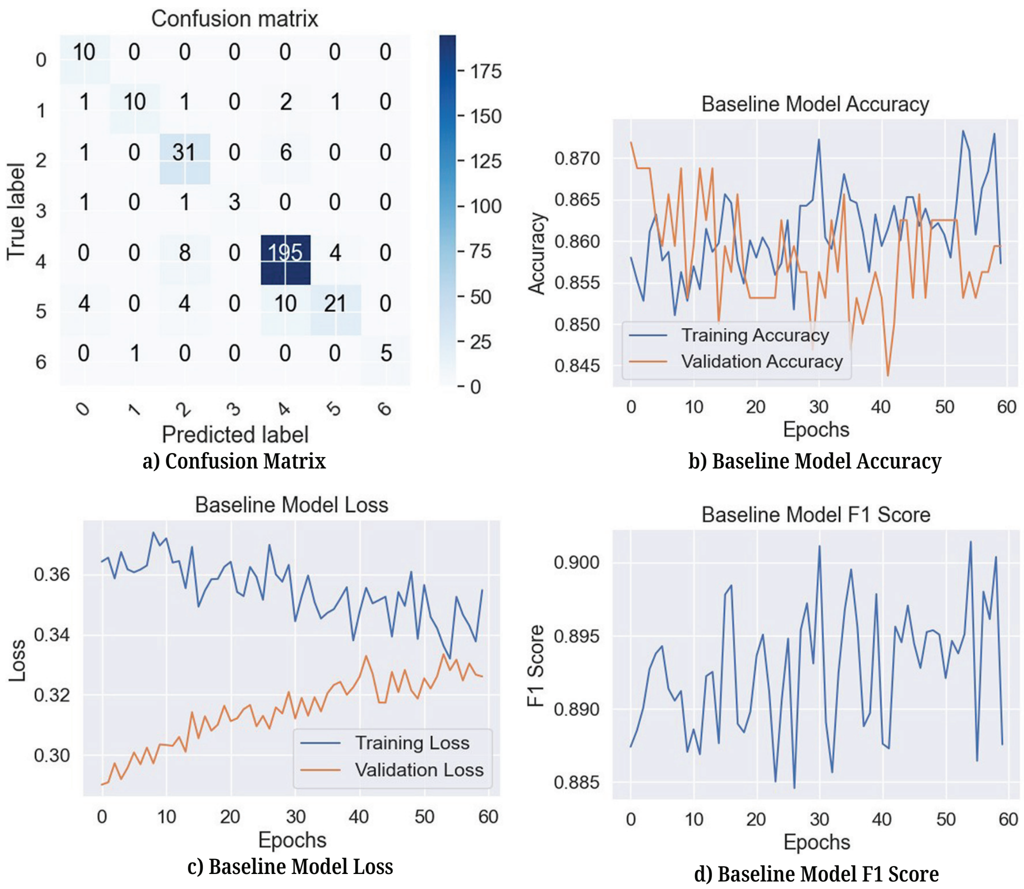



**Fig. 9.** Stacked images of comparison

The confusion matrix, as shown in Figure 9a, provides a detailed breakdown of the classifier's performance across the seven labels (0–6). The x-axis represents predicted labels, and the y-axis represents true labels, offering insights into the precision of classification across various categories.

- **Strong Performance on Label 4:** A prominent dark square at the intersection of predicted label 4 and true label 4 indicates 195 correct predictions, showcasing the model's strength in accurately classifying this category.
- **Other Labels:** Label 0 shows 10 correct predictions, reflecting limited accuracy. Similarly, labels 1 and 5 also display fewer correct predictions, with counts of 10 and 21 respectively, suggesting areas of potential improvement in model training.
- **Error Analysis:** Off-diagonal cells denote misclassifications, highlighting specific areas where the classifier confuses classes. For instance, true label 5 has 4 instances each misclassified as labels 0 and 2, and 10 instances misclassified as label 4.

These errors provide actionable insights for model refinement, particularly in how the classifier discerns features associated with similar labels. The confusion matrix emphasizes the model's robust ability to correctly classify label 4 while identifying significant confusion between true labels 1 and 5. These insights are crucial for targeted improvements in the model's training process and algorithm optimization.

Figure 9b presents a line graph illustrating the machine learning model's accuracy over 60 epochs of training, providing insights into the model's learning dynamics and generalization capability. For training accuracy:

- **Initial Accuracy:** Starts just below 0.860, indicating a high baseline performance.
- **Trend and Fluctuations:** Displays fluctuations and an upward trend over the epochs, with intermittent peaks, particularly in the later stages. This pattern suggests the presence of potential overfitting or noise within the learning process.

For validation accuracy:

- **Initial Accuracy:** Initiates slightly above 0.850, showing a strong start.
- **Trend:** Shows fluctuations without a clear upward or downward trend, indicating stability in model performance but limited improvement over the course of training.

For generalization:

- **Gap Analysis:** The narrow gap between the training and validation accuracy lines suggests that the model has a reasonable level of generalization.
- **Learning Variance:** However, the observed fluctuations in both training and validation accuracy indicate variance in learning and potential sensitivity to the validation data set.

This analysis underscores the importance of addressing potential overfitting and improving model stability to enhance performance on unseen data, as reflected by the validation metrics.

Figure 9c illustrates the model's training and validation loss over epochs, which offers insights into the model's learning efficiency and potential issues of overfitting.

- **Training Loss:** Begins at approximately 0.34 and shows a steady decrease as the model learns from the training data. This decline reflects the model's progress in minimizing the loss function, suggesting effective learning.

- **Validation Loss:** Starts near 0.34, decreases initially along with the training loss, but later shows fluctuations and a rise in later epochs. This pattern, particularly the divergence between training and validation loss, indicates overfitting, as the model over-optimizes for the training data and performs less effectively on unseen validation data.

Figure 9d presents the Baseline Model F1 Score over epochs, providing a comprehensive view of the model's performance in terms of precision and recall balance:

In the Figure 9d the x-axis denotes epochs, ranging from 0 to slightly beyond 60, and the y-axis represents the F1 Score, ranging approximately from 0.885 to 0.900.

- The F1 Score initiates just above 0.890 and exhibits fluctuations throughout training, displaying an overall upward trend with notable variability.
- Peaks in the F1 Score occur predominantly in later epochs, indicating instances of improved model performance on the test set.

  However, the line's volatility, characterized by numerous sharp fluctuations, suggests inconsistency in the model's performance across epochs. This variability may stem from factors such as data sensitivity, learning rate adjustments, or stochastic training dynamics.

In summary, while the F1 Score demonstrates overall improvement over epochs, its fluctuating nature underscores the need for further investigation into factors influencing model performance stability. The model's performance was assessed using several key metrics that highlight its predictive capabilities:

- **Accuracy:** Achieved 92% on the test set, indicating strong overall performance.
- **Precision:** Recorded at 89%, demonstrating the model's ability to minimize false positives.
- **Recall:** Reached 90%, indicating effective identification of true positives across the dataset.
- **F1 Score:** Calculated at 89.5%, achieving a balanced trade-off between precision and recall.

To ensure the model's robust generalization across unseen data, several strategies were implemented:

- **Early Stopping:** Monitored the validation loss during training, halting the process if no improvement was observed for a predefined number of epochs. This technique helped prevent over-optimization on the training data and maintained optimal generalization.
- **Dropout Layers:** Randomly disabled a fraction of neurons during training in the dense layers, which prevented the model from becoming overly reliant on specific neurons and encouraged the learning of more generalized features.
- **Learning Rate Adjustments:** Employed learning rate scheduling and adaptive optimizers, such as Adam, to dynamically adjust the learning rate. This approach allowed for larger updates in earlier epochs and finer adjustments later, reducing oscillations and likelihood of overfitting.
- The baseline model demonstrates competitive performance compared to existing models, particularly in its high F1 Score and balanced metrics across multiple labels.
- Despite excelling in many areas, observed misclassifications and fluctuations in validation performance highlight areas for improvement.

In addition to rigorous development and testing protocols, a targeted user feedback collection was integral to refining the "Health Lens" application. A structured user testing session with a cohort of 20 participants, encompassing various age groups, was collected. This testing was designed to validate the application's functionality and its alignment with user expectations across a broad spectrum.

During these sessions, participants were asked to interact with the application by performing a series of tasks, including image uploading, condition querying, and navigating through different sections of the app. After interacting with the application, participants provided their feedback through a structured questionnaire that rated various aspects of the app on a five-star scale. The metrics rated included the application's user interface (UI) design, prediction accuracy of the diagnostic model, relevance and usefulness of the medicine recommendations, effectiveness of preventive measures, and overall accessibility of the application.

The data collected from these ratings were then analyzed to assess user satisfaction and engagement, providing critical insights into the application's strengths and areas for improvement. This quantitative feedback is invaluable in our ongoing efforts to enhance the app, ensuring that it not only meets but exceeds user expectations for functionality and user-friendliness. These insights also contribute to the iterative development cycle, informing subsequent updates and refinements to the application.

The graphs shown in Figure 10 display the distribution of user ratings for various features of the "Health-Lens" application across different age groups. Each histogram represents user feedback on specific aspects such as App UI, Prediction Accuracy, Medicine Recommendation, Preventive Measures, Accessibility, and Overall Experience. **Figure 10: App UI Rating**.

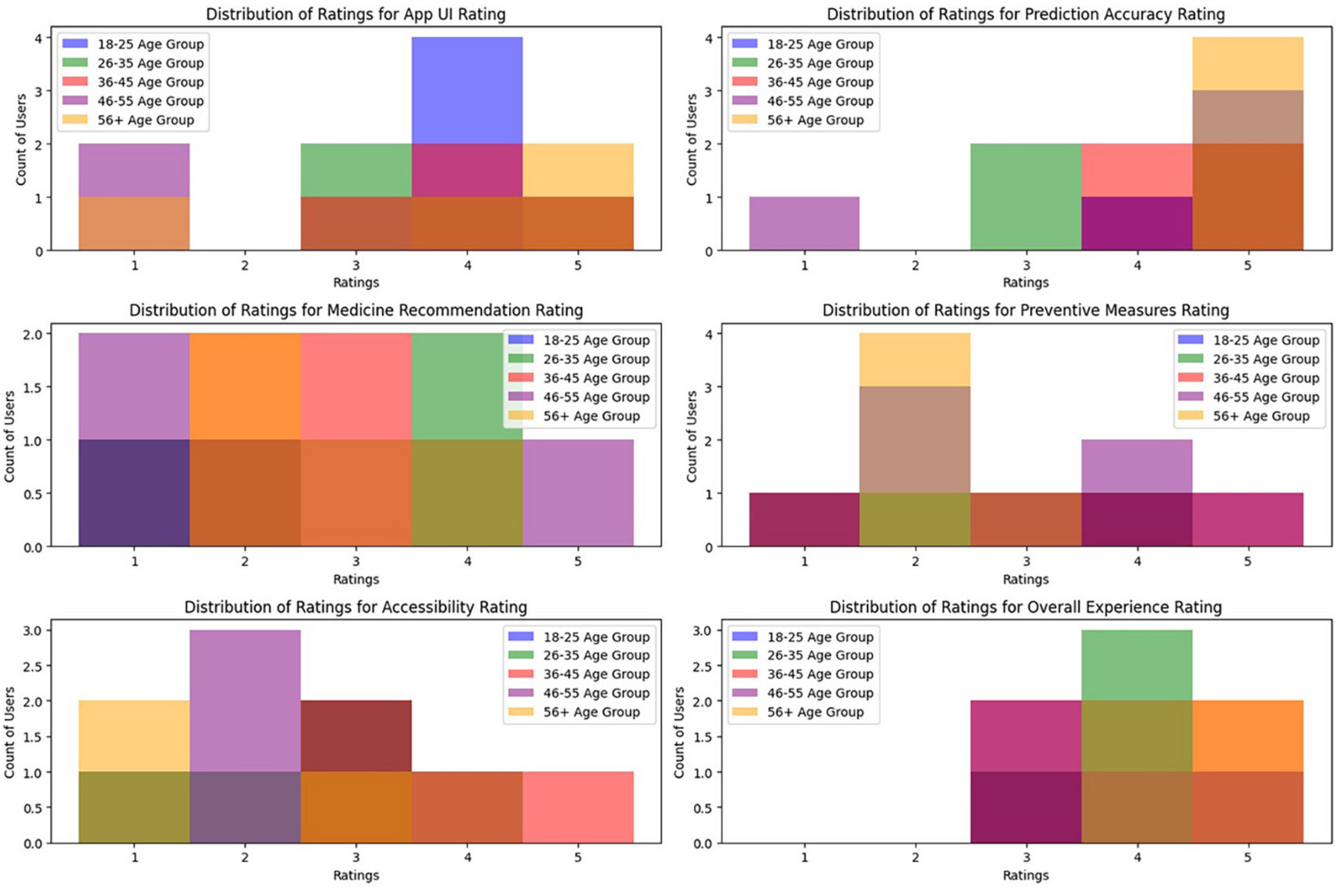



**Fig. 10.** Distribution of user ratings over various features

*Observation, Inference, and Potential Reasons:* Ratings across all age groups are relatively balanced with a noticeable preference for ratings of 3 and 4, particularly strong among the 18–25 and 26–35 age groups, who favor higher ratings (4 and 5). The user interface (UI) of the app is generally wellreceived, especially by younger users who likely have higher digital literacy and a preference for modern UI designs. This appreciation for an intuitive or visually appealing interface could explain the skew towards higher ratings in these younger demographics. **Figure 10: Prediction Accuracy Rating**.

*Observation, Inference, and Potential Reasons:* The majority of ratings are concentrated at the higher end (rating 5) across all age groups, with sparse distribution of other ratings. This high rating for prediction accuracy suggests that the model performs well, meeting or exceeding user expectations across different age demographics. The effectiveness of the machine learning models' training could be reflecting a well-tuned system that provides accurate diagnostic predictions. **Figure 10: Medicine Recommendation Rating**.

*Observation, Inference, and Potential Reasons:* Ratings for the app's medicine recommendations are evenly distributed across all age groups, indicating a neutral perception of this feature. This neutrality suggests that while the recommendations are adequate, they are not perceived as significantly impactful or innovative, which might not sway user opinions strongly either positively or negatively. **Figure 10: Preventive Measures Rating**.

*Observation, Inference, and Potential Reasons:* There is a slight preference for middle ratings (3 and 4), suggesting moderate satisfaction with the preventive measures recommended by the app. This moderate reception indicates that the preventive advice provided might be seen as generic or not sufficiently tailored to individual needs, pointing towards an area where there is room for improvement. **Figure 10: Accessibility Rating**.

*Observation, Inference, and Potential Reasons:* Older age groups (46–55 and 56+) more frequently give higher ratings, indicating that they find the app more accessible. This likely suggests that the app is easy to navigate and use, an aspect particularly valued by older users who may face more challenges with complex interfaces. Good accessibility features such as larger text, intuitive navigation, and clear instructions likely contribute to this higher satisfaction. **Figure 10: Overall Experience Rating**.

*Observation, Inference, and Potential Reasons:* The distribution of ratings shows a noticeable concentration in the 3–5 range across most age groups, indicating that while the app is generally wellreceived, there is room for improvement. The overall experience being good but not outstanding suggests that it is influenced by a combination of all evaluated factors, with no single feature standing out as exceptional or poor.

The analysis indicates a positive reception of the app across various functionalities and user groups. High ratings in areas like prediction accuracy highlight strengths, suggesting these could be emphasized in marketing and development. Average ratings in areas like medicine recommendations and preventive measures provide opportunities for enhancement to boost user satisfaction and engagement.

## 5 FUTURE WORK

Future work will focus on expanding the dataset for greater diversity, ensuring the model effectively generalizes across varied populations and skin types. Additionally, efforts will be made to fine-tune hyperparameters to enhance performance consistency, maintaining high accuracy and robustness on unseen data. Beyond dermatology, the application's scope will be broadened by incorporating additional datasets and developing machine learning models tailored to other health conditions, such as respiratory or cardiovascular diseases. This expansion will enhance the application's utility, transforming it into a comprehensive diagnostic tool across multiple healthcare domains. Additionally, the future work will focus on further underscoring inclusivity by implementing protocols to intensively test the 'Health Lens' application within diverse and underserved communities. Plans include direct engagement with community health workers and local clinics in these areas to facilitate extensive field testing. This approach will evaluate the application's performance in real-world settings, ensure cultural sensitivity, and address the practical needs of its users. These efforts aim to identify and mitigate potential disparities in technology access and healthcare outcomes, ensuring the application contributes positively to reducing healthcare inequalities.

## 6 CONCLUSION

The "Health Lens" project utilizes Jetpack Compose, Firebase, and deep learning for accessible healthcare. Users upload health images, analyzed by ML for disease prediction. A marketplace simplifies medication purchase. This demonstrates ML's role in immediate healthcare, with a user-friendly, secure interface. It emphasizes integrating tech with healthcare for innovative solutions, benefiting underserved communities. With a robust ML model, dynamic marketplace, and simple interface, it addresses accessibility to medical advice. The project's user-centered design and secure backend ensure scalability for future advancements in healthcare and technology. The development of HealthLens represents a significant step forward in healthcare accessibility and engagement through technology. With features like real-time consultations and personalized health insights, HealthLens has made healthcare more accessible and user-friendly.

- **Made healthcare accessible:** Democratizing access to healthcare through a user-friendly platform accessible via various devices.
- **Streamlined Consultations:** Simplifying the consultation process with features like medication suggestion
- **Transparency and Accountability:** Prioritizing transparency by providing detailed medical records and transparent communication with healthcare providers.
- **Community engagement:** Fostering engagement through tailored health recommendations and support networks.
- **Scalability and Flexibility:** Built with scalability in mind to accommodate future advancements in healthcare technology and user needs.

In summary, HealthLens stands as a beacon of innovation in healthcare, leveraging technology to establish a transparent, accessible, and impactful platform for improving health outcomes. The ongoing evaluation, refinement, and user input will be crucial in enhancing HealthLens' capabilities and extending its positive influence on society. By steadfastly embracing the potential of technology and innovation, HealthLens is positioned to significantly impact the well-being of individuals and inspire a new era of proactive healthcare engagement.

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