Health-Lens: A Health Diagnosis Companion

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1 Abstract

The "Health Lens" app emerges as a pivotal tool in advancing healthcare accessibility and promoting Sustainable Development Goals (SDGs) by democratizing healthcare access and leveraging advanced machine learning (ML) capabilities. Through its user-friendly interface and robust technology stack including Jetpack Compose and Firebase, the app empowers users to make informed health decisions by providing immediate healthcare assessments, particularly in underserved areas. By addressing **SDG 3** (Good Health and Well-being) and **SDG 10** (Reduced Inequalities), the app fosters accessibility to medications and bridges gaps in healthcare access. By integrating comprehensive features for dermatological diagnostics and patient management, "Health Lens" fills a significant research gap, offering a unified platform for accurate disease identification, personalized medical advice, efficient disease management, medication purchase, and curated information about skin diseases. Overall, "Health Lens" contributes to promoting healthier communities worldwide by leveraging technology to enhance healthcare accessibility.

1.1 Keywords

Healthcare accessibility, Sustainable Development Goals (SDGs), Advanced machine learning (ML), Neural networks (CNN), User-friendly interface Underserved areas,SDG 3 (Good Health and Well-being), SDG 10 (Reduced Inequalities) Dermatological diagnostics, Disease identification, Personalized medical advice

2 Introduction

"Health-Lens" is an innovative android application designed to revolutionize the way individuals approach healthcare. Utilizing Kotlin Jetpack Compose, Flask API, and Firebase, this project integrates a deep learning model to offer instant preliminary diagnoses based on user-uploaded images of their health conditions. Alongside, it provides detailed descriptions of diseases and their symptoms, empowering users with valuable health insights. Aimed at enhancing healthcare accessibility and efficiency, "Health Lens" bridges the gap between technology and well-being, providing a seamless, user-friendly platform for immediate health assessments and information.

3 Literature Survey

3.1 Research Gap

- The research gap addressed by the proposed work lies in the integration of comprehensive features in dermatological diagnostics and patient management within a mobile app framework.
- Existing studies have explored disease identification [1], but a unified platform is needed for accurate identification, personalized medical advice, irrespective of skin color, and user history tracking for efficient disease management. The existing works have been able to successfully classify the diseases, [2], Drug references have been suggested in [3], invariance of the predictions to skin color have been considered in [4], mitigation techniques for the predicted diseases have been proposed in [5]. History of the diseases has been shown in [5], marketplace does not exist in any of the surveyed applications. News and information about the diseases have been included in the application by [6].
- The proposed work also facilitates medication purchase and offers curated news and information about skin diseases, bridging the gap between dermatological research and practical healthcare solutions.

3.2 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.

Papers	Identification[10]	Class[6]	Drug Ref.[7]	Skin color[4]	Mitigation[7]	History[7]	Marketplace	News[12]	Info[6]
[1]	✓	×	×	×	×	×	×	×	×
[2]	✓	✓	×	×	×	×	×	×	×
[3]	✓	✓	✓	×	×	×	×	×	×
[4]	✓	✓	×	✓	×	×	×	×	×
[7]	✓	×	×	×	×	×	×	×	×
[8]	✓	✓	×	×	×	×	×	×	✓
[5]	✓	✓	✓	×	✓	✓	×	×	×
[9]	✓	✓	×	×	×	×	×	×	×
[10]	✓	✓	×	×	✓	×	×	×	×
[11]	✓	✓	×	×	×	×	×	×	×
[12]	✓	✓	×	×	×	×	×	×	×
[6]	×	×	×	×	×	×	×	✓	✓
Proposed Work	✓	✓	✓	✓	✓	✓	✓	✓	✓

3.3 Contribution/Novelty

[1] Sahin et al. proposed a method for classifying human monkeypox using skin lesion images. Their approach leveraged a deep pre-trained network through a mobile application, showcasing the potential of mobile platforms in dermatological diagnostics.

[2] Mustapha et al. introduced DIdiagnosis, a versatile mobile and web application designed for disease classification using deep learning. The study emphasizes the role of technology in providing accessible healthcare solutions.

[3] Pires et al. conducted a comprehensive investigation into the classification and applicability of mobile health applications. The research sheds light on the broader landscape of mobile health technologies, including those related to dermatology.

[4] Chan et al. discussed the current applications, opportunities, and limitations of machine learning in dermatology. The paper provides insights into the advancements and challenges in applying machine learning to dermatological diagnoses.

[5] Ng et al. focused on developing a mobile application for plant disease detection using deep learning. While the primary focus is on plant diseases, the study contributes to the broader context of mobile applications in disease identification.

[6] Sallam and Ba Alawi proposed a mobile-based intelligent system for skin diseases diagnosis. The study highlights the potential of mobile applications equipped with intelligent algorithms in facilitating skin disease diagnosis.

[7] The Plantifyai application, as presented in this paper, utilizes convolutional neural networks for crop disease detection. The study showcases the role of advanced technologies in agriculture through mobile applications.

[8] Elhassouny and Smarandache proposed a smart mobile application for recognizing tomato leaf diseases using convolutional neural networks. The study demonstrates the application of deep learning in agriculture through mobile platforms.

[10] Tembhurne et al. focused on plant disease detection using a deep learning-based mobile application. The research contributes to the growing field of agricultural technology by leveraging artificial intelligence for disease identification.

[9] This research focuses on supporting sustainable development goals through a gamified mHealth application for people with albinism in Africa. While not directly related to dermatology, the study explores the use of mobile health applications for specific communities.

[11] Isa et al. present a mobile health tracker application for children, applying soft system methodology for community IT based projects. While focusing on pediatric health, the research explores the use of mobile applications in community-based healthcare projects.

[12] Martinez-Perez et al. conduct a review on mobile apps in cardiology, offering insights into the broader landscape of mobile applications in healthcare. The research provides a foundational understanding of mobile health applications beyond dermatology

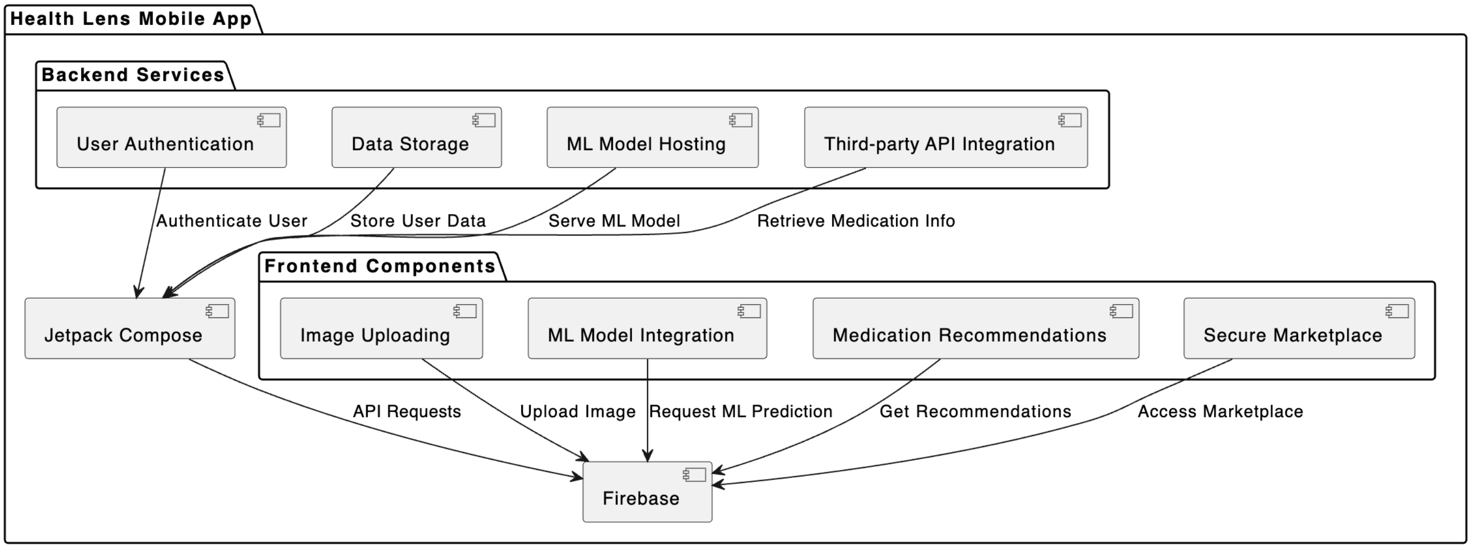

Figure 1: Architecture Diagram

4 Methodology

Dataset: The ISIC 2019 dataset has been used to classify the skin images.

Kaggle link: https://www.kaggle.com/datasets/bhanuprasanna/isic2019

Needs Assessment: Conducting a thorough analysis of healthcare accessibility challenges, focusing on underserved communities and their requirements for immediate healthcare assessments.

Technology Selection: Evaluated various mobile development frameworks and technologies, opting for Jetpack Compose for the frontend and Firebase for backend services due to their scalability, ease of use, and integration capabilities.

Machine Learning Model Development: Collaborating with healthcare professionals to identify key parameters for disease prediction. Developing and training a robust machine learning model using a diverse dataset of health condition images.

App Development: Employing an iterative development approach, starting with basic features and gradually incorporating advanced functionalities such as image uploading, ML model integration, medication recommendations, and suggestion of mitigation techniques.

User Testing and Feedback: Conducting user testing sessions with individuals to gather feedback on usability, interface design, and overall user experience.

Documentation and Reporting: Documented the entire development process, including methodologies, references, solutions implemented, and lessons learned, culminating in the preparation of this comprehensive report.

4.1 LLD

The Low-Level Design of the "Health Lens" app outlines the intricate details of its functionality and structure. It delineates modules such as user authentication, image processing, ML model integration, medication recommendations, and backend services. Interfaces between these modules are defined, specifying data formats and communication protocols. Data structures, algorithms, and error handling mechanisms are detailed to ensure efficient processing and robust performance. Dependencies on external libraries and APIs are documented. Visual diagrams illustrate the flow of data and interactions between components. This comprehensive design serves as a blueprint for developers to implement the application’s features effectively.

4.2 HLD

The High-Level Design (HLD) of the "Health Lens" app provides a broad overview of its 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 manage user authentication, data storage, 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. The HLD serves as a roadmap for building a robust, scalable, and user-friendly application, aligning with the project's objectives and requirements.

5 Results

The HealthLens Android application effectively predicts skin conditions based on uploaded images of affected areas. It accurately identifies conditions including Actinic keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanocytic nevus, Melanoma, Squamous cell carcinoma, and Vascular lesion. The key findings include

- **Accuracy**: HealthLens demonstrates high accuracy and precision in disease prediction due to rigorous training on diverse datasets.
- **User Engagement**: Users find the process intuitive, uploading images and receiving prompt disease predictions and suggested medications, enhancing satisfaction.
- **Disease Identification**:The application proficiently identifies a wide array of skin diseases, empowering users to take proactive health measures.
- **Medicine Suggestions**: HealthLens recommends personalized medication based on the identified condition, aiding users in managing their health concerns effectively.
- **Impact**: The deployment of HealthLens holds promise in revolutionizing dermatological care, facilitating early detection, and potentially reducing healthcare burden

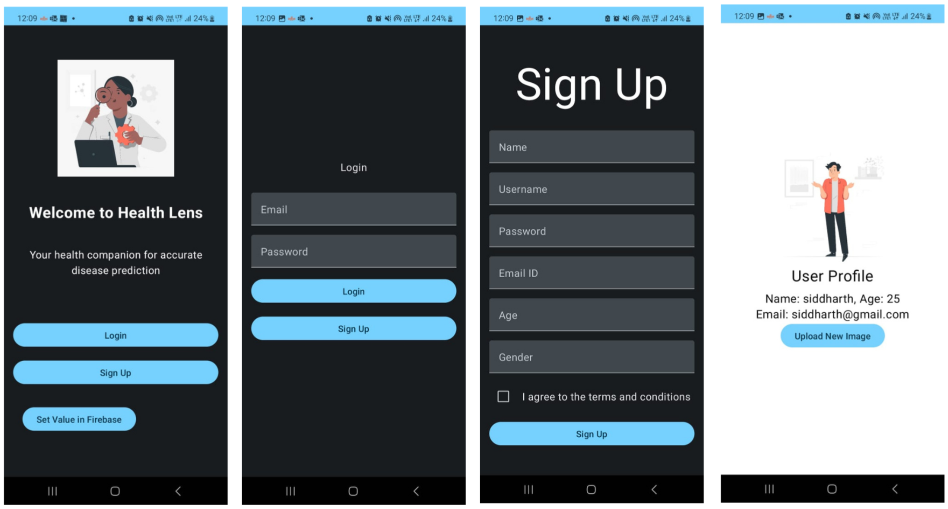

Figure 2: (a) Homepage (b) Login (c) Sign-up (d) User dashboard

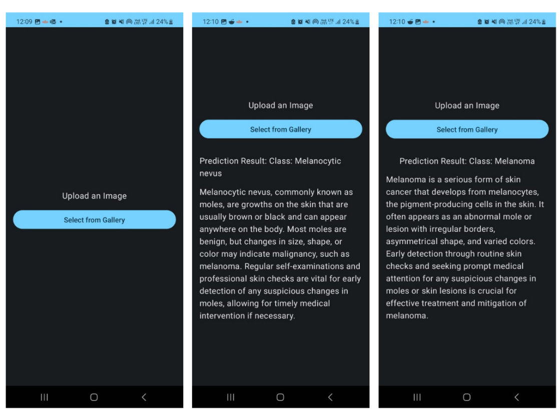

Figure 3: (a) Disease Upload Screen (b)(c) Disease identification

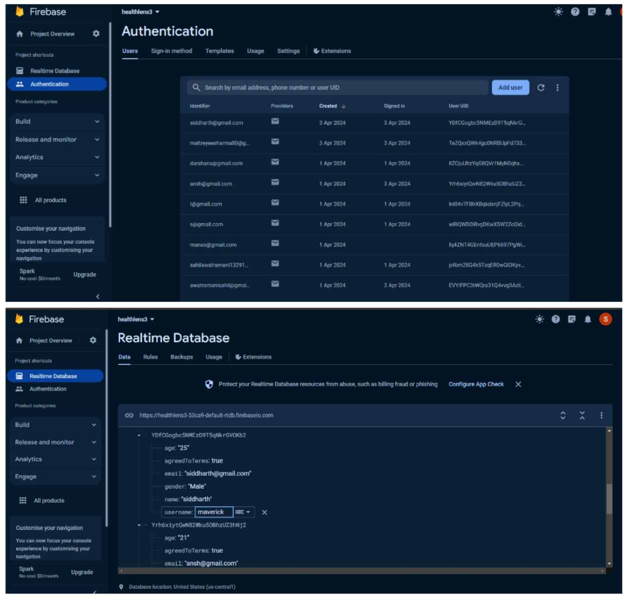

Figure 4: (a)User Authentication database (b)Realtime Database

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

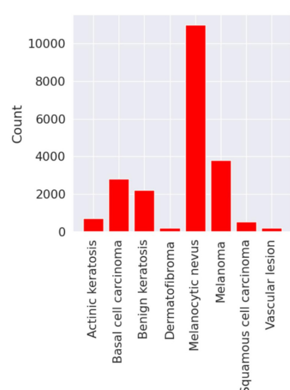

Figure 5: (a)Model Architecutre (b)Classes v/s sample data count

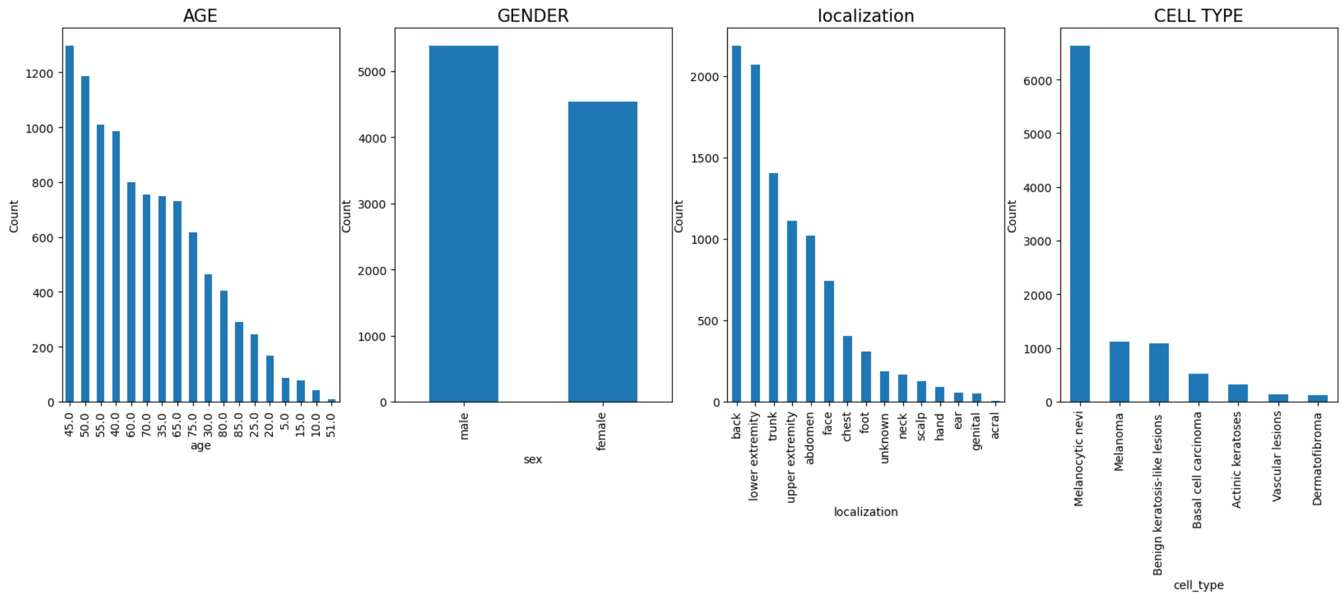

Figure 6: (a) AGE (b) GENDER (c) LOCALIZATION (d) CELL TYPE

AGE:The bar chart delineates age along the x-axis, while the y-axis depicts the frequency of observations. A progressive decline in bar height from left to right implies a higher concentration of observations within younger age brackets, diminishing as age increases.

GENDER: The bar chart illustrates two bars denoting "male" and "female" genders, respectively. The y-axis denotes the frequency of observations. Both bars exhibit considerable heights, with the male bar slightly surpassing the female counterpart. This suggests a comparable distribution between male and female counts, albeit with a marginal predominance of males.

LOCALIZATION: The x-axis delineates various body locations, while the y-axis indicates the frequency of observations. The 'back' and 'lower extremity' exhibit notably higher counts compared to other localizations, with a tapering off in counts for other regions.

CELL TYPE:The bar chart enumerates different cell types, depicting disease names along the x-axis. The y-axis denotes the frequency of observations. "Melanocytic nevus" emerges with a notably higher count compared to other cell types, indicating a substantial margin of prevalence, while the remaining cell types exhibit significantly lower counts.

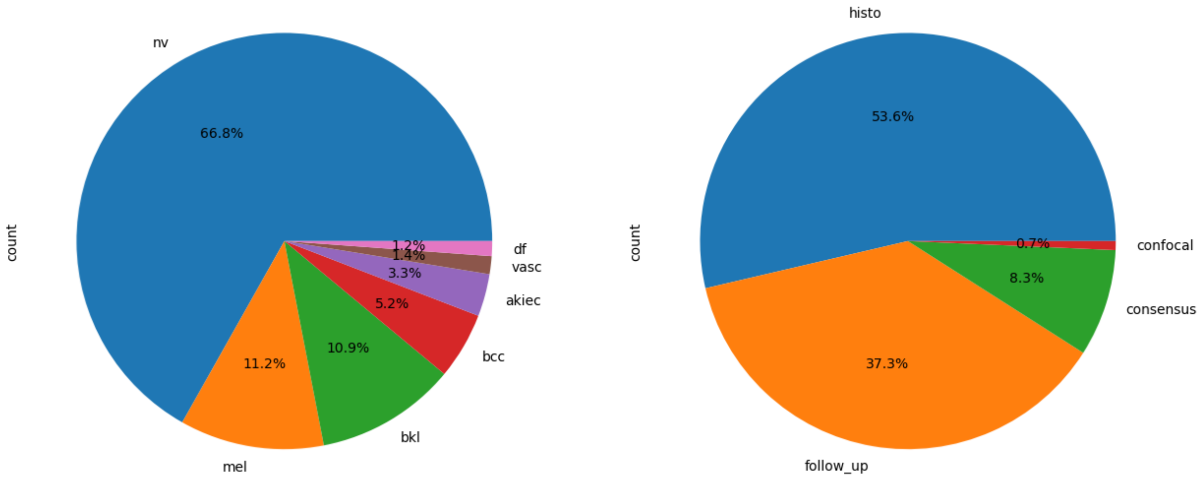

Figure 7: (a)Number of Diseases in Dataset (b)Diagnosis Techniques

Figure 7a: The dominant element in this chart is a sizable blue segment labeled "nv," occupying 66.8% of the chart's area. This indicates the prevalence of "nv" within the dataset. Additionally, smaller segments include "mel" (11.2%), "bkl" (10.9%), "bcc" (5.2%), "akiec" (3.3%), "vasc" (1.4%), and "df" (1.2%).

Figure 7b: Within this chart, the largest segment is labeled "histo", representing 53.6% of the chart. Subsequently, the "followup" segment constitutes 37.3%. The remaining segments are "consensus" (8.3%) and "confocal" (0.7%).

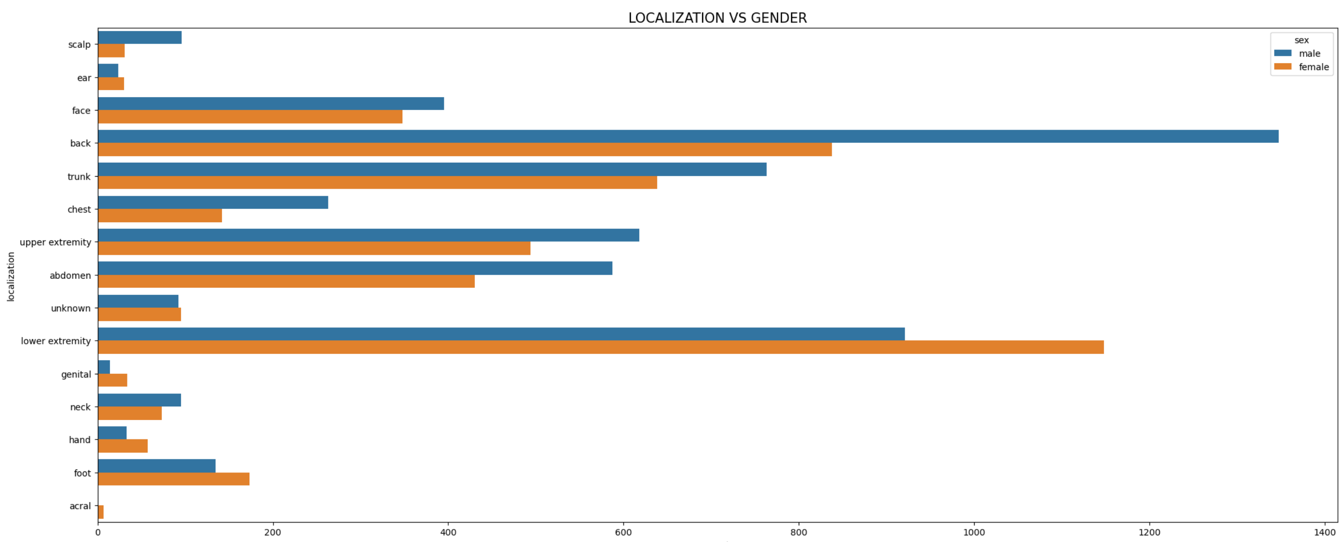

Figure 8: (a)Localization versus Gender

Figure 8 compares the count of observations across different localizations for males and females. The y-axis lists various anatomical localizations, including scalp, ear, face, back, trunk, chest, upper extremity, abdomen, unknown, lower extremity, genital, neck, hand, foot, and acral.

The x-axis represents the count of observations, ranging up to over 1200 in some categories. Each localization has two bars adjacent to it: one blue (male) and one orange (female), indicating the counts for each gender. Generally, the blue bars (male) exceed the orange bars (female), particularly notable in the "back", "trunk", "upper extremity", and "lower extremity" categories. The "lower extremity" exhibits the highest counts for both genders, with male counts exceeding 1200 and female counts approaching that figure, suggesting it as the most common localization. Conversely, the "acral" category shows the lowest counts for both genders.

These results underscore gender differences in observed counts across anatomical localizations, highlighting disparities in distribution between males and females.

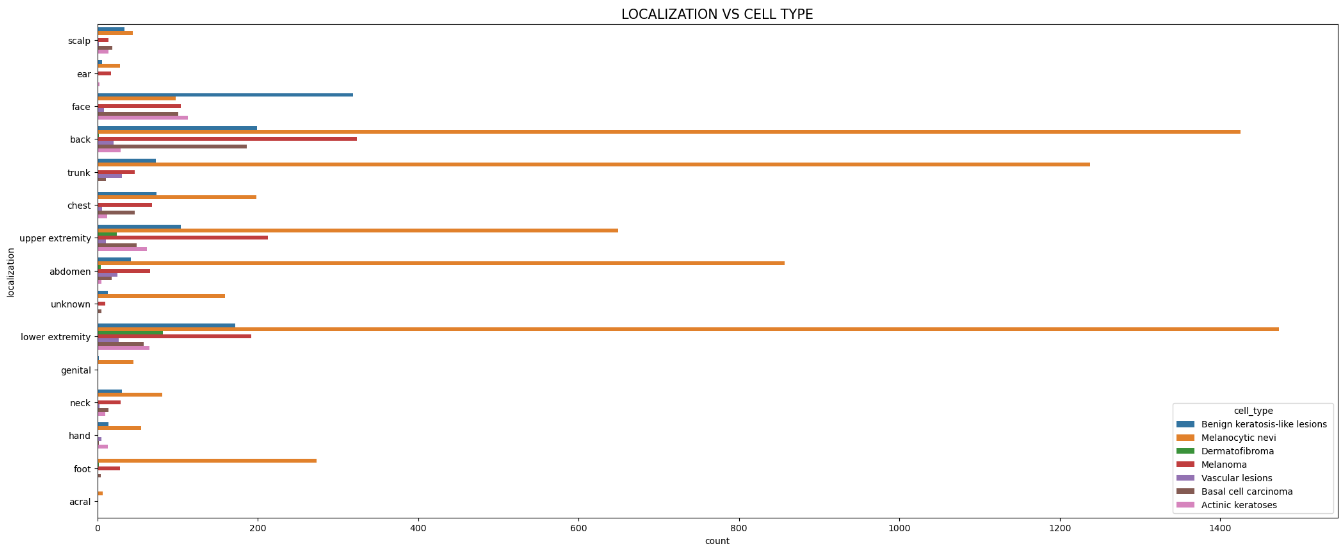

Figure 9: Localization vs Cell Type

Figure(a) illustrates the distribution of different cell types across various body localizations. The y-axis enumerates the localizations, including scalp, ear, face, back, trunk, chest, upper extremity, abdomen, unknown, lower extremity, genital, neck, hand, foot, and acral. Meanwhile, the x-axis quantifies the occurrences or observations. Several patterns emerge from the figure Benign keratosis-like lesions (blue) and Basal cell carcinoma (orange) dominate most localizations. Melanocytic nevi (green) are more prevalent in the lower extremity and back. Melanoma (red) and Actinic keratoses (dark red) show notable presence in certain localizations but are less dominant overall. Dermatofibroma (purple) and Vascular lesions (teal) appear less frequently across all localizations. Notably, the "lower extremity" exhibits the highest counts for several cell types, particularly for Basal cell carcinoma (orange), which stands out with a significantly longer bar. These observations shed light on the distribution patterns of different cell types across body localizations, providing valuable insights into their prevalence and occurrence. This visualization serves as a useful tool for understanding the relationship between cell types and their localization on the body.

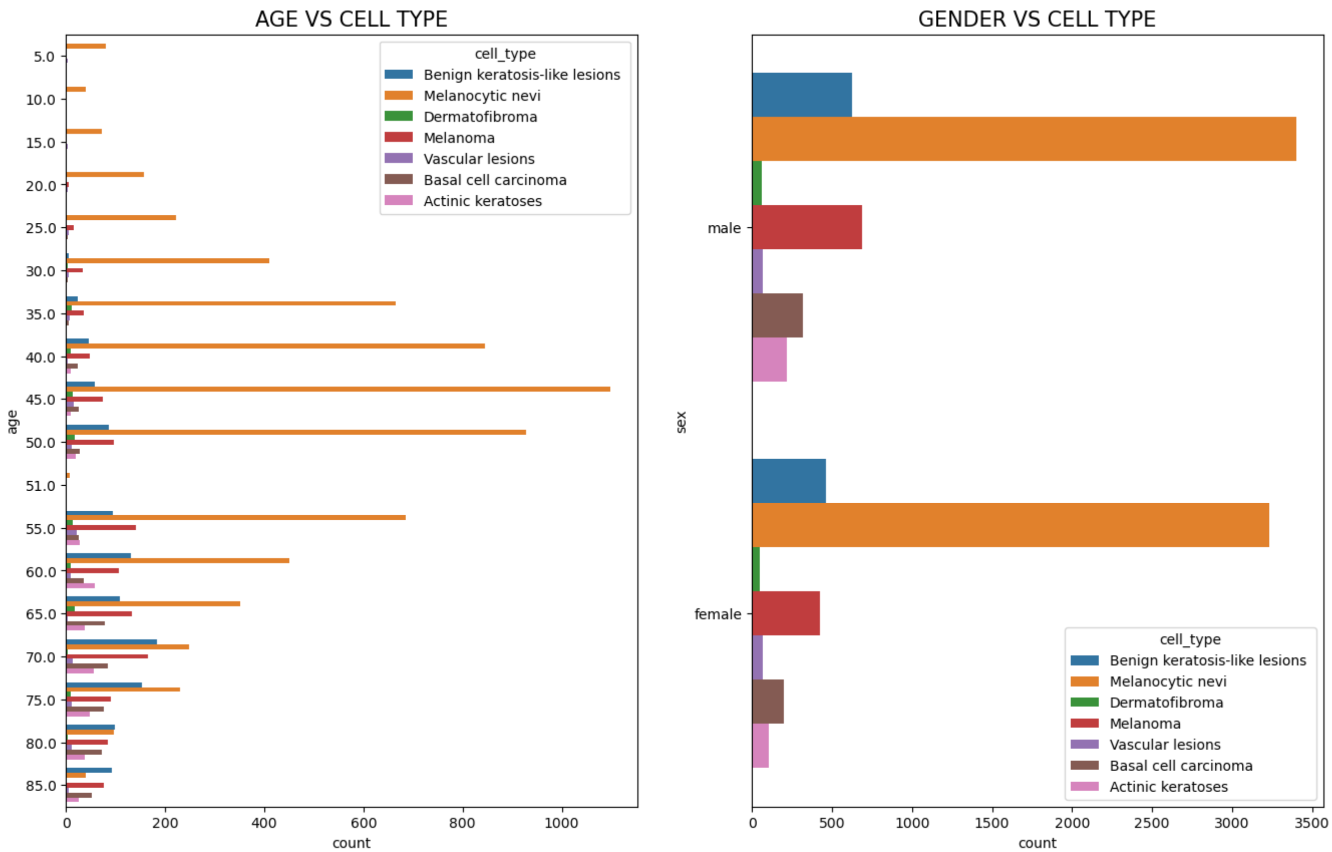

Figure 10: (a)Age vs Cell Type (b)Gender vs Cell Type

Figure(a) showcases the distribution of various cell types across different age groups. The y-axis delineates age groups in 5-year increments, ranging from 0 at the bottom to 85 at the top. Meanwhile, the x-axis represents the count of observations. Each cell type is color-coded for clarity, as outlined in the legend. Observations from this chart indicate that basal cell carcinoma (brown) is more prevalent in older age groups, notably peaking around the ages of 60-65. Benign keratosis-like lesions (blue) also exhibit higher occurrence rates in older individuals. Conversely, melanocytic nevi (orange) are distributed across all ages, with a slight increase observed in middle age. Figure(b) represents the count of various cell types categorized by gender. Here, the y-axis separates genders, with male at the top and female at the bottom. The x-axis, akin to Figure(a), represents the count of observations. Figure(b) reveals that benign keratosis-like lesions (blue) and basal cell carcinoma (brown) manifest higher counts in males compared to females. Similarly, melanocytic nevi (orange) and dermatofibroma (green) are more prevalent in males, while melanoma (red) shows slightly higher counts in females. Notably, vascular lesions (purple) and actinic keratoses (pink) exhibit comparable counts across genders.

Both charts facilitate the comparison of cell type prevalence across age groups and genders, providing valuable insights for medical research and understanding demographic trends in dermatological conditions.

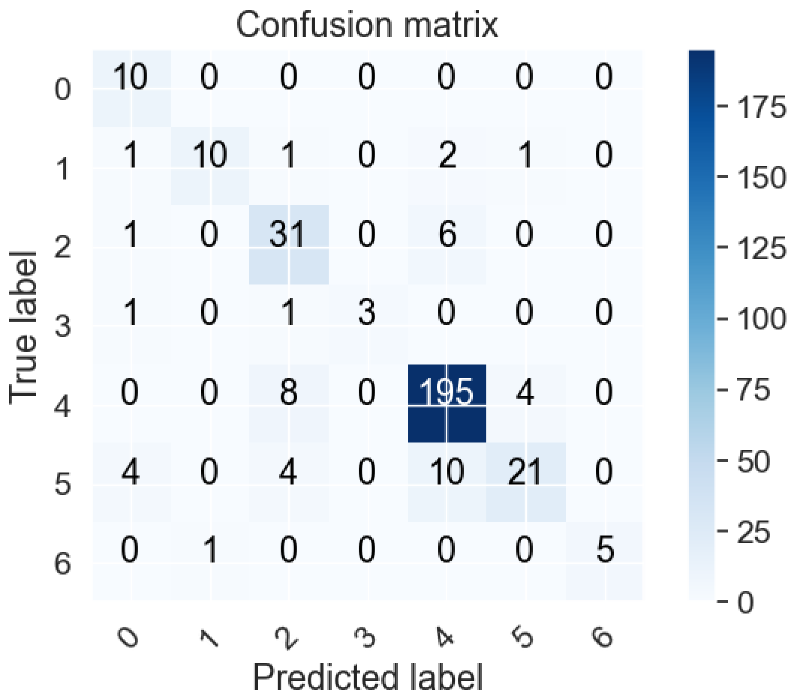

Figure 11: Confusion Matrix

Key observations from the confusion matrix include:

- The x-axis denotes predicted labels ranging from 0 to 6, while the y-axis represents true labels from 0 to 6.
- Each cell in the matrix signifies the count of predictions for a specific true label and predicted label pair, with darker shades indicating higher counts, as indicated by the color bar on the right side.

Highlighted findings within the matrix are as follows:

- A prominent dark square at the intersection of predicted label 4 and true label 4, indicating 195 correct predictions for this category.
- Label 0 exhibits 10 correct predictions.
- Labels 1 and 5 have fewer correct predictions, with counts of 10 and 21, respectively, along with misclassifications distributed across other labels.
- Off-diagonal numbers signify misclassifications. For instance, true label 5 has 4 instances each predicted as labels 0 and 2, and 10 instances predicted as label 4.

The confusion matrix serves to identify classification errors and pinpoint instances where the classifier confuses two classes. Correct classifications align with the diagonal from top left to bottom right, while off-diagonal cells denote misclassifications. Darker cells represent higher counts of observations falling into specific categories. In summary, the classifier excels in correctly predicting label 4 and performs reasonably well on label 3. However, some confusion between classes is evident, particularly involving true labels 1 and 5, where misclassifications are more dispersed.

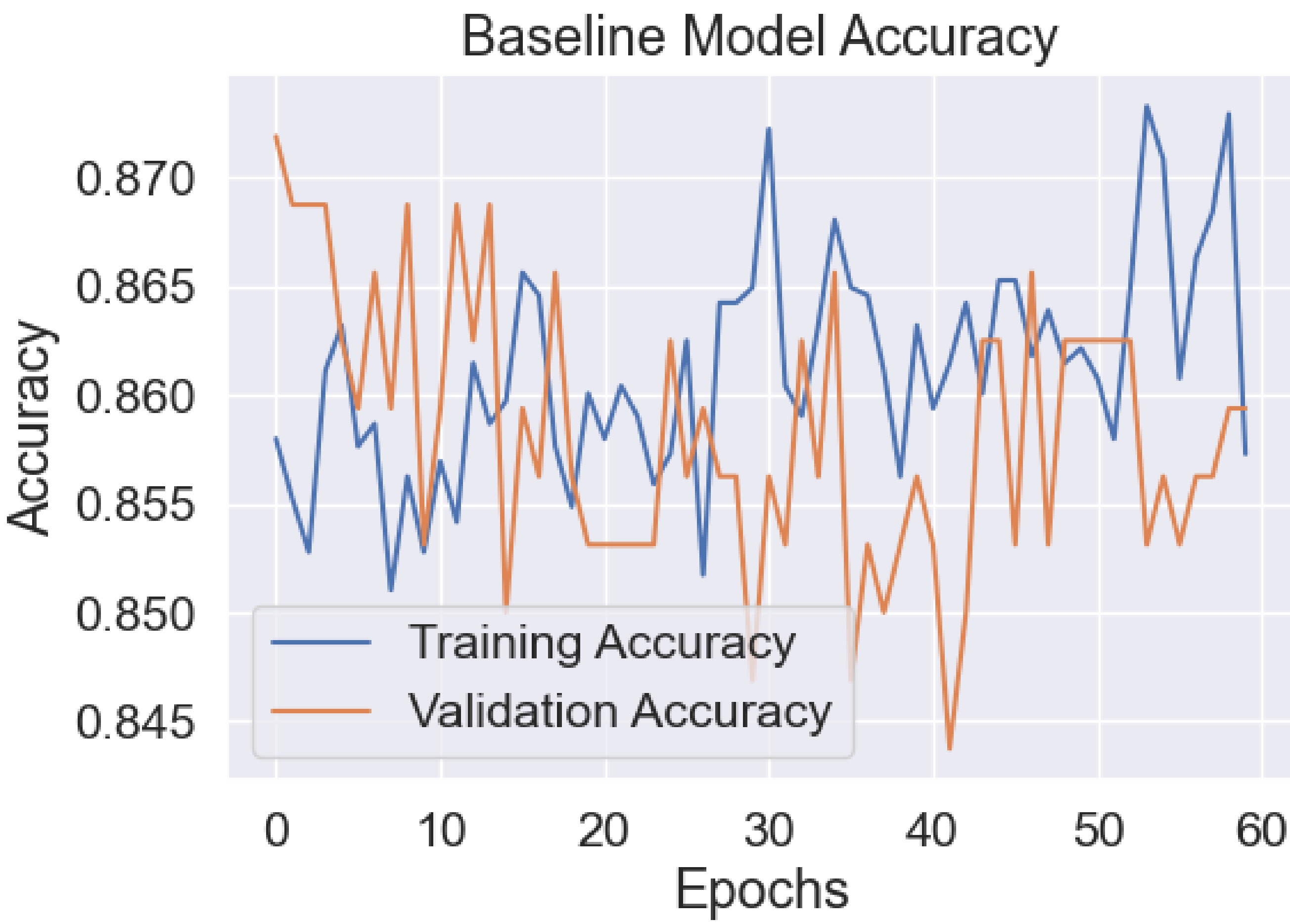

Figure 12: Baseline Model Accuracy

The figure depicts a line graph illustrating the accuracy of a machine learning model across multiple epochs of training. An epoch represents a complete iteration through the training dataset.

- Training Accuracy initiates just below 0.860 and exhibits fluctuations throughout epochs, generally trending upwards with intermittent peaks, particularly in later epochs, indicating potential overfitting or noise.
- Validation Accuracy begins slightly above 0.850 and displays fluctuations without a discernible trend, suggesting the model's stability or lack of significant improvement or deterioration on the validation set during training.
- The narrow gap between Training and Validation accuracy lines implies reasonable generalization of the model. However, fluctuations and peaks may signify variance in the learning process or response to validation data. The objective of training is to achieve high accuracies with minimal gap, reflecting robust performance that generalizes effectively to unseen data.

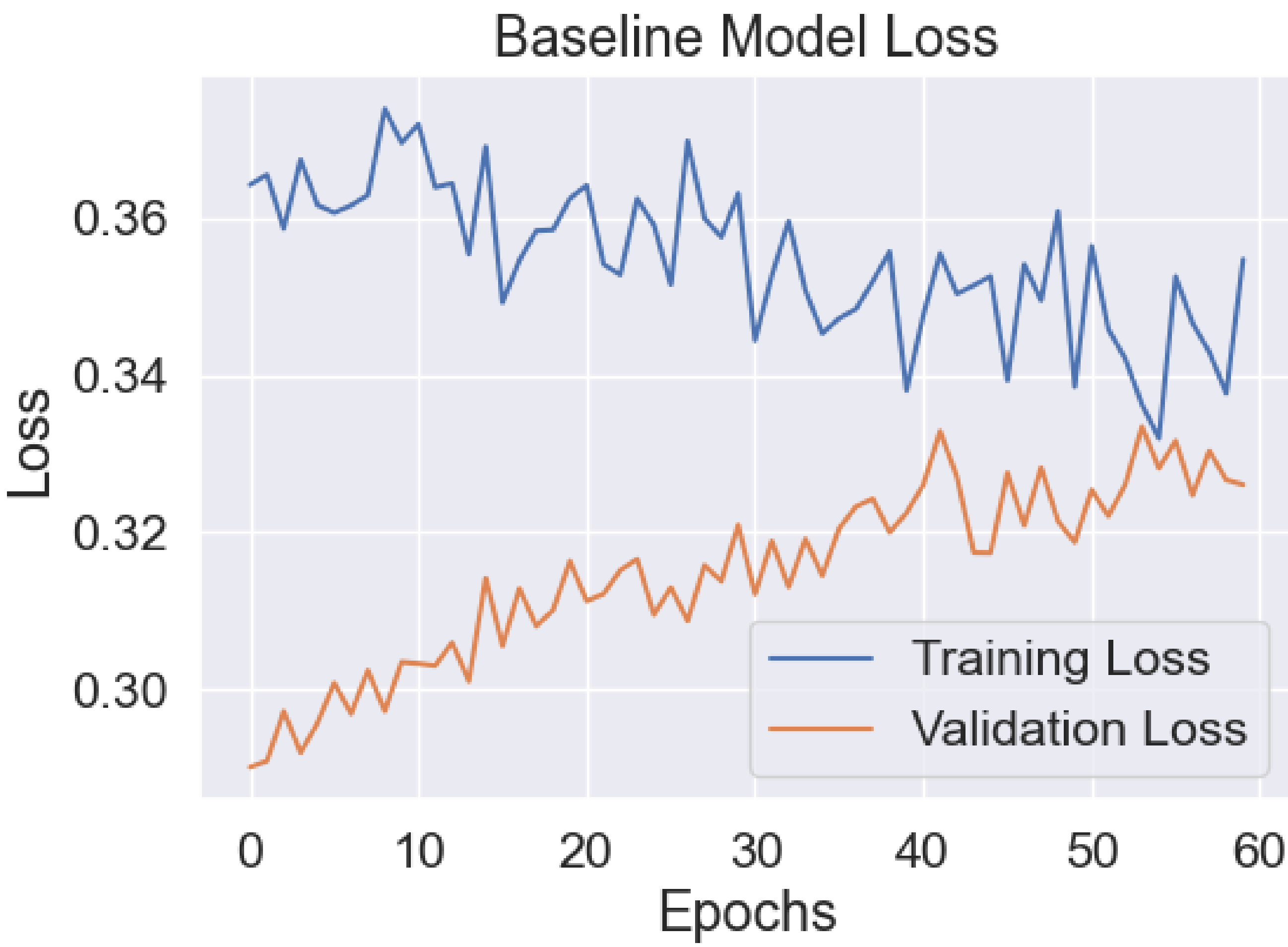

Figure 13: Baseline Model Loss

The above figure represents a line graph titled "Baseline Model Loss," illustrating the loss of a machine learning model across epochs during training. The x-axis denotes epochs, ranging from 0 to slightly beyond 60. The y-axis signifies loss values, ranging approximately from 0.30 to 0.36.

- Training Loss initiates around 0.34 and steadily decreases as epochs progress, indicative of the model learning from the training data.
- Validation Loss starts near 0.34 and initially decreases, reflecting model improvement on the validation set. However, it later fluctuates and rises towards later epochs, implying potential overfitting.
- The divergence between Training and Validation Loss becomes more pronounced in later epochs, suggesting overfitting as the model performs better on training data compared to unseen validation data.

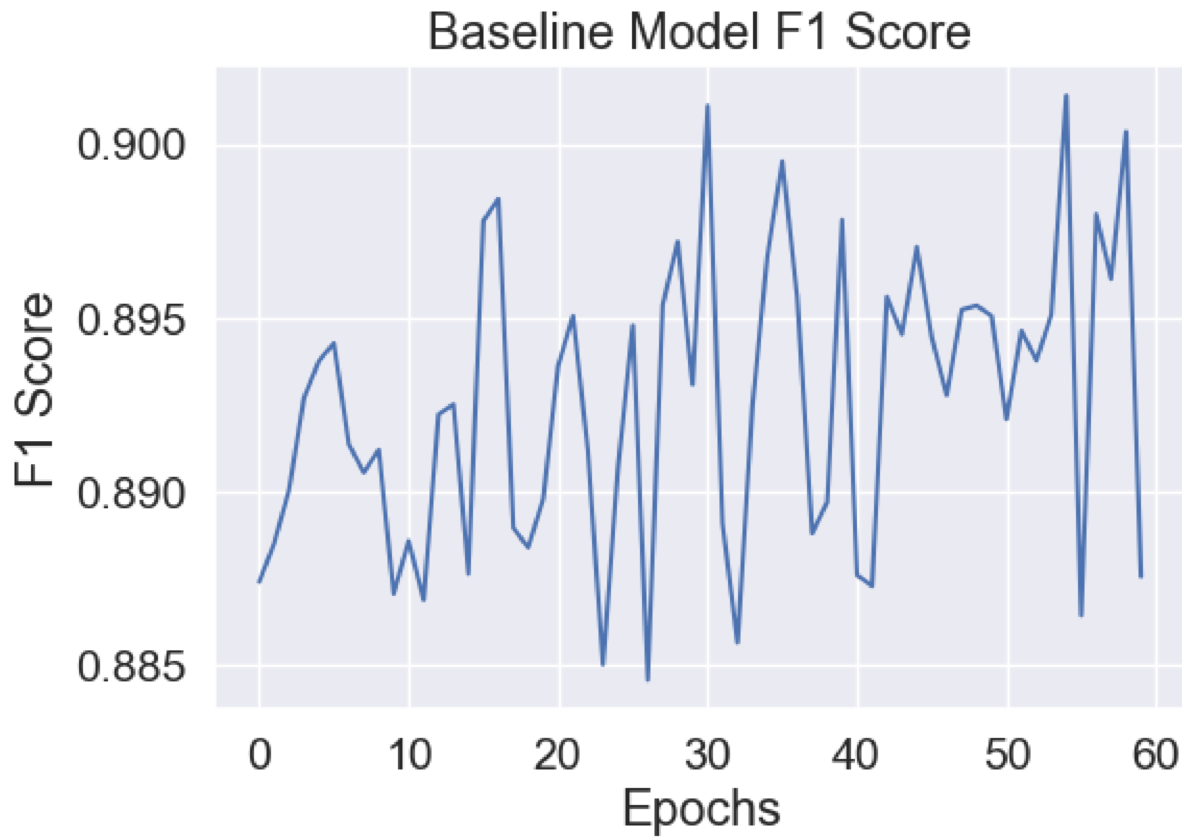

Figure 14: Baseline Model F1 Score

In the above figure 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.

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. As we look ahead, 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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7 Other References

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