CSE4077 - RECOMMENDER SYSTEMS

J COMPONENT REPORT

SKIN HEALTH PREDICTION APP

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Submitted to

Dr. K. PRADEEP

DECLARATION

I hereby declare that the report titled **"SKIN HEALTH PREDICTION APP"** submitted by us to VIT Chennai is a record of bona-fide work undertaken by me under the supervision of **Dr. K. PRADEEP**, School of Computer Science and Engineering, Vellore Institute of Technology, Chennai.

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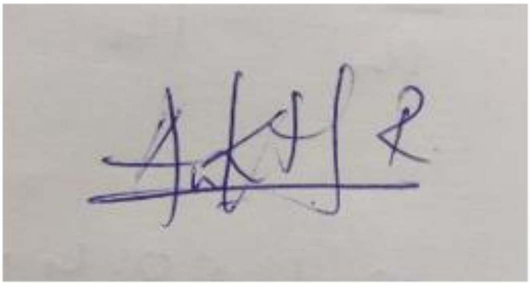

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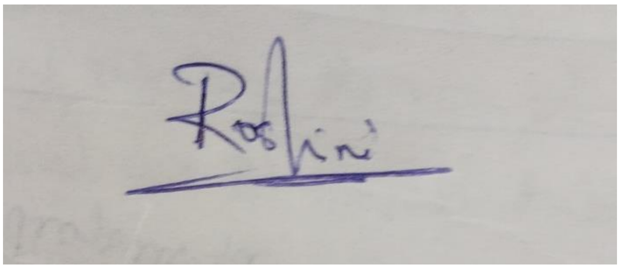

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CERTIFICATE

Certified that this project report entitled **"SKIN HEALTH PREDICTION APP"** is a bonafide work of ANUKEERTHI R (Reg. No. 20MIA1160), SHIVA SINDHU PERLA (Reg. No. 20MIA1104) and ROSHINI R (Reg. No. 20MIA1171) and they carried out the Project work under my supervision and guidance for **RECOMMENDER SYSTEMS**.

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Abstract

The Skin Health Prediction App is a cutting-edge solution specifically designed to improve the diagnosis and management of melanoma, a serious and potentially fatal skin cancer. By harnessing the strengths of advanced machine learning and mobile technology, the app is intended to offer users precise and timely skin health evaluations. Melanoma, defined by the uncontrolled proliferation of pigment-producing cells, can quickly metastasize to other regions of the body if not identified early. Early diagnosis is crucial, yet many people face significant barriers to accessing dermatological care, including the high cost of consultations, limited availability of specialists, and geographic challenges, particularly in rural or underserved areas.

The app employs a sophisticated Convolutional Neural Network (CNN) model to analyze user-submitted images of skin lesions. This deep learning algorithm, trained on a comprehensive dataset of labeled melanoma images, offers precise categorization of skin conditions. Users can easily capture and upload photos of suspicious moles or lesions through the app. The CNN model then processes these images, providing an accurate diagnosis and categorizing the condition as benign or malignant, which is critical for melanoma management.

In addition to diagnostic capabilities, the app offers several features to support users in managing their skin health. It helps users locate and book appointments with nearby dermatologists and clinics for further evaluation. For those unable to visit a clinic, the app facilitates virtual consultations, allowing users to receive professional medical advice remotely. Furthermore, the app provides prescription guidance, suggesting over-the-counter and prescription treatments, and offers educational resources on melanoma and other skin conditions, empowering users with essential information about prevention and care.

By integrating state-of-the-art technology with accessible healthcare solutions, the Skin Health Prediction App aims to improve early detection of melanoma, enhance treatment outcomes, and ultimately save lives. It marks a considerable advancement in enhancing the accessibility, efficiency, and effectiveness of dermatological care for individuals at risk of melanoma globally.

Keywords: *Convolutional Neural Network (CNN), melanoma, Skin Health Prediction App, Dermatologist, Clinic Recommendations, Firebase Databases, Cloud-Based Storage*

1. Introduction

1.1 Introduction to Skin Health Issues

Skin is the biggest organ of the human body, serving as a protective barrier against environmental threats and is integral to overall health and wellness. Skin conditions can greatly affect an individual's quality of life, causing physical discomfort, psychological stress, and, in severe cases, serious health complications. Common skin issues include acne, eczema, psoriasis, dermatitis, and skin cancer. These conditions often manifest in visible symptoms such as rashes, lesions, discoloration, and swelling, which can be both painful and stigmatizing for affected individuals. The visibility of these conditions can lead to embarrassment and social isolation, further affecting the mental health of those affected.

Despite the prevalence of skin diseases, many people lack access to timely and precise diagnosis and treatment. Factors contributing to this issue include a shortage of dermatologists, high costs of medical consultations, and geographic barriers, especially in rural or underserved areas. The limited availability of specialized dermatological care means that many patients must travel long distances to see a dermatologist, which can be both time-consuming and costly. This lack of access often results in delays in diagnosis and treatment, allowing skin conditions to worsen and potentially lead to more severe health issues.

Additionally, the proliferation of misinformation and self-diagnosis through unreliable internet sources can lead to incorrect treatments, potentially exacerbating skin conditions. Many people seek answers online, where they often find inaccurate or misleading information. Relying on this information for self-diagnosis and self-treatment can lead to the use of unsuitable remedies that may not resolve the underlying issue or could even cause harm. This highlights the necessity for reliable and accessible tools that provide accurate diagnosis and treatment recommendations, ensuring individuals receive the proper care and guidance for their skin health.

1.2 Importance of timed and correct prognosis

Timed and correct analysis of skin situations is vital for numerous reasons. Early detection and appropriate treatment can prevent skin conditions from worsening and reduce the danger of headaches. as an instance, early-stage pores and skin cancer may be handled greater successfully than advanced levels, notably enhancing the diagnosis for patients. accurate diagnosis guarantees that sufferers get hold of the maximum appropriate remedy for their unique condition, leading to higher health results and quicker restoration.

This precision in remedy now not best complements the effectiveness of clinical interventions however also reduces the likelihood of complications that may arise from incorrect or behind schedule remedy. furthermore, early and accurate prognosis can notably reduce healthcare charges by means of addressing pores and skin troubles directly, as a consequence minimizing the need for luxurious treatments and hospitalizations. by using stopping the development of skin illnesses to greater excessive degrees, patients can avoid extended and expensive scientific interventions, contributing to extra green use of healthcare sources. proper control of pores and skin situations also can alleviate signs and symptoms consisting of pain, itching, and discomfort, enhancing the affected person's quality of lifestyles and mental well-being.

effective remedy regimens that are tailored to the affected person's particular needs can assist manipulate chronic signs, reduce physical soreness, and improve general fine of lifestyles. moreover, accurate diagnosis helps keep away from the dangers associated with misdiagnosis and incorrect remedies, that can every so often purpose unfavourable results or fail to address the underlying problem. Misdiagnosis can lead to irrelevant remedies that won't most effective be ineffective however also doubtlessly dangerous, exacerbating the circumstance or inflicting extra fitness issues.

therefore, a reliable diagnostic system is critical to ensure that patients acquire the right remedy and keep away from the terrible effects of incorrect medical interventions.

1.3 Overview of the Skin Health Prediction App

The Skin Health Prediction App is an innovative solution designed to address the challenges associated with skin disease diagnosis and treatment. Leveraging advancements in machine learning and mobile technology, the app aims to provide users with convenient access to accurate skin health analysis and medical guidance.

The core functionality of the app involves the use of a Convolutional Neural Network (CNN) model, a type of deep learning algorithm particularly effective in image analysis tasks. Users can capture and upload images of their skin issues through the app. The CNN model then analyzes those photographs, correctly categorizing the skin condition primarily based on a full-size dataset of labeled skin disorder snap shots.In addition to providing diagnostic results, the app offers several other features to enhance user experience and support skin health management:

- **Nearby Dermatologists and Clinics**: The app helps users find and book appointments with local dermatologists and skin clinics for further evaluation.
- **Virtual Consultations**: Users can connect with dermatologists for remote consultations, receiving professional medical advice without the need to visit a clinic.
- **Prescription Guidance**: The app suggests over-the-counter and prescription alternatives for common skin problems, providing accessible and cost-effective treatment options.
- **Educational Resources**: Users have access to information about various skin conditions, treatments, and preventive care measures.

2. Objectives

2.1. Develop an Accurate Skin Condition Classification Model

The cornerstone of the Skin Health Prediction App is its ability to accurately identify and categorize a wide range of skin conditions based on user-submitted images. The CNN model leverages a large, curated dataset of skin condition images to learn and distinguish between different types of skin issues.

2.2. Create a User-Friendly Mobile Application

A critical aspect of the Skin Health Prediction App is its user-friendly mobile application. The app is designed to allow users to easily capture and upload images of their skin issues. The intuitive interface guides users through the process of taking clear and focused pictures, which are essential for accurate diagnosis. The model undergoes great training up to date make certain high accuracy and reliability in its predictions, making it a precious up to date for early detection and prognosis of skin conditions.

The training process involves feeding the version with lots of classified snap shots, allowing it up to date research the diffused differences and styles up-to-date numerous skin conditions. The deployment of the version guarantees that up-to-date technique images submitted by users in actual-time, offering on the spot comments and prognosis. up to date updates and retraining of the model with new records make sure that it remains with the modern medical information and may handle emerging skin situations.

2.3. Ensure Data Privacy and Security

Given the sensitive nature of health-related data, ensuring the privacy and security of the skin health prediction app is of utmost importance. The app prioritizes user data security by implementing advanced encryption and secure storage protocols. The organization ensures strict adherence to privacy regulations, including the general data protection regulation (gdpr) and the health insurance portability and accountability act (hipaa).

User data, such as images and personal information, is safely stored in a cloud-based database that automatically syncs in real-time. Only individuals with proper authorization can access this data, and strict security protocols are implemented to ensure that unauthorized access is prevented. Consistent security assessments and updates guarantee that the app stays protected against new threats, providing users with reassurance that their information is secure.

2.4. Facilitate Access to Professional Medical Advice

The skin health prediction app seeks to connect users with professional medical guidance, filling the gap between the two. The app offers convenient ways for users to connect with dermatologists, guaranteeing that they can receive expert advice on their skin issues. The app includes a directory of nearby clinics, making it convenient for users to locate and schedule appointments with dermatologists without any hassle. For individuals who prefer remote consultations, the app provides virtual consultation options, allowing users to connect with dermatologists from the convenience of their own homes.

This feature is especially advantageous for individuals residing in remote or underserved regions, where access to dermatologists may be scarce. The app's partnership with healthcare providers guarantees that users receive prompt and precise medical guidance, enhancing their skin health and averting the worsening of skin conditions.

2.5. Promote Preventive Skin Care

Beyond diagnosis and treatment, the Skin Health Prediction App is committed to promoting preventive skin care. The app provides users with valuable information and tips on maintaining healthy skin and preventing common skin conditions. This includes guidance on daily skincare routines, sun protection measures, and lifestyle changes that can improve skin health.

Educational content is regularly updated to reflect the latest dermatological research and best practices. By empowering users with knowledge, the app aims to reduce the incidence of preventable skin conditions and promote long-term skin health. Preventive care not only benefits users but also reduces the burden on healthcare systems by minimizing the need for treatment of avoidable conditions.

2.6. Continuous Improvement

To stay effective and up-to-date, the skin health prediction app regularly seeks user input and incorporates advancements in machine learning into its ongoing enhancement process. User feedback is gathered through different channels, such as in-app surveys and interactions with customer support. This feedback is incredibly valuable in pinpointing areas that require improvement and enhancing the app's functionality.

The app frequently incorporates the latest developments in machine learning to enhance the precision and effectiveness of the skin condition classification model. The app's development team keeps up with the latest research and technological advancements, guaranteeing that the app remains at the forefront of skin health technology. This dedication to ongoing enhancement guarantees that users always have access to the most effective tool for maintaining their skin health.

3. Literature Review

Sl.No.	PAPER TITL	YEAR	AUTHOR	JOURNAL NAME	ALGORITHMS	PARAMETERS	ADVANTAGES	DISADVANTAGES
1.	Skin Cancer Disease Detection Using Transfer Learning Technique	2022	Javed Rashid, Maryam Ishfaq, Ghulam Ali, Muhammad R. Saeed, Mubasher Hussain, Tamim Alkhalifah, Fahad Alturise, Noor Samand	Applied Sciences	MobileNet V2 for melanoma classification using transfer learning	Includes learning rate, batch size, number of epochs, augmentation techniques, etc.	The proposed deep learning technique outperforms state-of-the-art deep learning techniques in terms of accuracy and computational cost. MobileNetV2 optimizes execution speed and memory consumption at a minimal cost with respect to the error.	High-quality medical imaging datasets for training are still scarce. CNN with simple architecture is more likely to overfit on limited training datasets.
2.	Primary Vulval Melanoma and Genital Lichen Sclerosus	2024	Evanthia Mastoraki, Georgios Kravvas, Kate Dear, Sharmaine Sim, Mariel James, Richard Watchorn, Aiman Haider, Peter Ellery, Alex Freeman, Mahfooz Basha, Emma Edmonds, Christopher B. Bunker	Skin Health and Disease	Not applicable as the study involves clinical review and literature analysis	Histopathological features, clinical records, and literature data	The study suggests a potential causative relationship between genital lichen sclerosus (LS) and vulval melanoma, as indicated by the presence of genital LS in 64% of the vulval melanoma cases. The findings have implications for the early diagnosis, management, and follow-up of genital LS.	The study is limited by its size, the retrospective collection of data, and the lack of clinical photographs. The histopathology findings may have been distorted by subjectivity.

3	Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM	2021	Parvathaneni Naga Srinivasu, Jalluri Gnana SivaSai, Muhammad Fazal Ijaz, Akash Kumar Bhoi, Wonjoon Kim, James Jin Kang	Sensors	MobileNet V2 and Long Short-Term Memory (LSTM)	Various parameters discussed in the methodology and performance evaluation sections, including learning rate, batch size, and number of epochs.	Efficient in maintaining stateful information for precise predictions, Works on lightweight computational devices, Better accuracy compared to other state-of-the-art models, Minimal computational efforts	Needs considerable computational efforts for GLCM, Characteristics are not invariant with rotation and texture changes
4.	Skin Cancer Detection Using Image Processing	2017	Uzma Bano Ansari, Tanuja Sarode	International Research Journal of Engineering and Technology (IRJET)	Image Processing and Support Vector Machine (SVM)	Grayscale conversion, noise removal, image enhancement, segmentation using maximum entropy thresholding, feature extraction using GLCM, SVM for classification	Early detection of skin cancer is possible at the initial stage, which is more advantageous to patients. Skin cancer detection using SVM can prevent the unnecessary excision of perfectly harmless moles and skin lesions. Accuracy of the proposed system is 95%.	The study is limited by the availability of high-quality images for processing. There is a risk of misclassification due to variations in image quality and preprocessing techniques.
5.	Skin Lesion Classification Using CNN With Novel Regularizer	2019	M. A. Albahar	IEEE Access	CNN with novel regularizer	Novel regularizer based on the standard deviation of the weight matrix, convolution layers, ReLU activation	The proposed model produced a maximum average accuracy of 97.49%. The proposed CNN model has lesser computational	It cannot be used for feature selection or feature reduction. Choosing a suitable value of λ is difficult, as it is a continuous value and attempting a

							complexity and better generalization capability than other models.	million times to select a single suitable value is computationally expensive and time-intensive.
6.	Skin Lesion Detection Using Hand-Crafted and DL-Based Features Fusion and LSTM	2022	Rabbia Mahum, Suliman Aladhadh	Diagnostics	Local Binary Patterns (LBP), Inception V3, Long Short-Term Memory (LSTM)	•Gaussian Filtering (GF) for noise removal •Local Binary Patterns (LBP) for hand-crafted feature extraction •Inception V3 for automatic feature extraction •Adam optimizer for learning rate adjustment	Our proposed model attained 99.4% accuracy, 98.7% precision, 98.66% recall, and a 98% F-score. Employed 750 images for training, with an equal distribution of 375 malignant and 375 benign images. Achieved considerable results with a small number of training samples due to transfer learning-based algorithms. Experimental assessments showed our proposed model attained the best detection accuracy compared to existing techniques.	Automated methods based on hand-crafted feature extraction may fail to detect skin cancers at an early stage when tested on unseen data. X-ray mammography is painful, making advanced microwave imaging techniques preferred.
7.	Ensemble-Based CNN Models for Melanom	2019	Eduardo Perez, Sebastian Ventura	Neural Computing and Applications	Ensemble of CNN models	Various CNN models, including DenseNet, MobileNet, InceptionV3,	All models achieved the best performance using segmented	UDA-2 was the most challenging dataset. On average, the models achieved only 44% MCC.

	a Detection					SGD, RMSprop, Adam, Nadam optimizers	data, and on average the best ones were MobileNet, DenseNet, and InceptionV3, in that order. The proposed segmentation method obtained the best average performance in both datasets with 81% and 80% UNS in PH2 and DERM-LIB, respectively.	CNN models can learn from a wide variety of nonlinear data points. As such, they are prone to overfitting on datasets with small numbers of samples per category, thus attaining a poor generalization capacity.
8.	Skin Cancer Detection System Project	2024	Riya Jaiswal, Sakshi Singh, Vishal Gupta, Ms. Isha Gupta	International Journal of Research Publication and Reviews	Convolutional Neural Networks (CNN), K-Nearest Neighbors (KNN)	Image preprocessing, segmentation, feature extraction, CNN model training, KNN classification	The CNN model proposed in this study is a deep learning model that performs very well in imaging such as cancer screening. Early diagnosis is very important in the treatment of skin cancer. The system provides a user-friendly GUI interface for loading, preprocessing, training, and skin cancer diagnosis and classification using CNNs.	Due to the complexity of the relationship involving approximately 25,000 images in the HAM10000 dataset, a total of 800 images were considered for tracking 200 images per category. It should not completely replace medical personnel-based diagnosis.

9.	Skin Disease Prediction	2023	D. Jena Catherine Bel, Bharath P, Edwin Mathews, Nidharshana B, Monika R	International Journal for Multidisciplinary Research (IJFMR)	Convolutional Neural Network (CNN) for image classification. Softmax used for multi-class classification. Machine learning model built for better accuracy. Deep learning used to train the model.	Filters: Specific features in the image (edges, lines, textures) Activation Function: ReLU (Rectified Linear Unit) Pooling Layer: Reduces the size of feature maps Fully Connected Layer: Weights applied to generate final output Softmax Function: Converts final output into a probability distribution	Skin disease prediction models may provide personalized treatment recommendations based on a patient's skin type, medical history, and other factors. With the increasing availability of large datasets and advances in computer vision and AI technologies, skin disease prediction models are becoming more accurate and reliable.	There are still challenges to overcome, including the need for standardized datasets and the difficulty in differentiating between similar skin diseases. Despite these challenges, skin disease prediction using machine learning is a promising area of research that has the potential to improve patient outcomes and increase access to care.
10.	Automatic Classification of Melanoma Skin Cancer with Deep Convolutional Neural Networks	2019	Khalil Aljohani, Turki Turki	AI	Various CNN architectures (DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, GoogleNet)	Dataset: 7146 images from the ISIC dataset, 4522 of which are relevant to melanoma skin cancer. Image size: 224 × 224 pixelsTools: Python, TensorFlow, Keras, Google Colaboratory	Facilitates accurate and swift decision-making in medical diagnostics. Helps overcome limitations in human experience and decision speed. Makes the diagnostic process more accessible and efficient for patients.	Requires extensive amounts of data for effective training. Dependence on high-quality hardware, like GPUs, which can be costly. Susceptibility to noise in medical images, impacting feature extraction and potentially leading to training inaccuracies.
11.	Discriminative	2020	Belal Ahmad,	IEEE Access	Deep Convolutio	Fine-tuning of	Outperforms state-of-the-	Slower convergence due

	Feature Learning for Skin Disease Classification Using Deep Convolutional Neural Network		Mohd Usama, Chuen-Min Huang, Kai Hwang, M. Shamim Hossain, and Ghulam Muhammad		nal Neural Network (CNN) fine-tuned ResNet152 and InceptionResNet-V2 with a triplet loss function	ResNet152 and InceptionResNet-V2 layers, Triplet loss function, 128-D embeddings in Euclidean space, L-2 distance calculation, Learning rate: 0.0001, Momentum: 0.8	art methods in skin disease classification. Utilizes standard feature extraction methods and well-known classifiers like SVM and ANN, enhancing effectiveness.	to inactive triplets during training, necessitating the selection of active, hard triplets. Risk of generating indecisive results in small mini-batches when choosing the hardest negative triplet, potentially leading to poor network performance initially.
12.	Classification of Melanoma Skin Cancer using Convolutional Neural Network	2019	Rina Refianti, Achmad Benny Mutiara, Rachmadinna Poetri Priyandini	International Journal of Advanced Computer Science and Applications (IJACSA)	Convolutional Neural Network (CNN) with LeNet-5 architecture	LeNet-5 architecture, Training with 176 images and 100 epochs, Python programming language, Keras library with TensorFlow backend	Uses deep learning technology with Convolutional Neural Network (CNN) method. Utilizes LeNet-5 architecture for image data classification. Achieved 93% success in training and 100% in testing with 44 images using varying training sets and epochs.	Difficult to compare different classification methods due to non-public datasets used in some approaches. Lack of reproducibility in studies using non-public datasets for training and testing. Calls for future publications to adopt publicly available benchmarks and disclose training methods for better comparability.
13.	Convolutional Neural Network (CNN) for Automati	2020	Yunendah Nur Fu'adah, NK Caecar Pratiwi, Muhammad	IOP Conference Series: Materials Science	Convolutional Neural Networks (CNN)	Layers (input, convolution, activation, pooling, fully connected), hyperparame	The proposed model uses the Adam optimizer and achieves an accuracy of	The system models using SGD, RMSprop, and Nadam optimizers for training and

	c Skin Cancer Classification System		Adnan Pramudito, Nur Ibrahim	and Engineering		ters (optimizers: SGD, RMSprop, Adam, Nadam)	99%. The model is not overfitting and can recognize dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma with 99% accuracy. The system is promising for use by medical personnel in diagnosing skin cancer or benign tumors.	validation data can decrease suddenly, indicating overfitting. Errors occurred in four images of nevus pigmentosus detected as melanoma and six images of melanoma detected as nevus pigmentosus.
14.	Intelligent System for Skin Disease Prediction using Machine Learning	2021	Ahmed A. Elngar, Rishabh Kumar, Amber Hayat, Prathamesh Churi	Journal of Physics: Conference Series	Convolutional Neural Network (CNN) combined with Support Vector Machine (SVM) (CNN-SVM-MAA)	Convolutional Layer, Activation Function: ReLU, Pooling Layer, Fully Connected Layer, Softmax Function	Early identification and treatment of diseases facilitated by the system. Utilization of a modified pre-trained CNN and SVM algorithm enhances disease detection. CNN integrates linear and non-linear processes for effective analysis.	Challenges include the need for standardized datasets. Difficulty in distinguishing between similar skin diseases. Complexity in early detection and classification of skin diseases. Histogram equalization may not always improve contrast and can sometimes worsen it.
15.	A Web-Based Skin Disease Diagnosis Using Convolutional	2019	Samuel Akyeramfo-Sam, Acheampong Addo Philip, Derrick Yeboah,	International Journal of Information Technology and	Convolutional Neural Network (CNN)	Convolutional Layer Activation, Function: ReLU, Pooling Layer, Fully	Enhanced accuracy and faster diagnosis compared to traditional methods. Trustworthy	Continued reliance on manual visual clues by most dermatologists in Ghana. Limited sample data availability

	Neural Networks		Nancy Candylove Nartey, Isaac Kofi Nti	Computer Science (IJITCS)		Connected Layer, Softmax Function	and resourceful for dermatological disease detection. Real-time learning platform for students studying dermatology.	from medical centers affecting study data size.
16.	Melanoma Skin Cancer Detection using Image Processing and Machine	2019	Vijayalakshmi M M	International Journal of Trend in Scientific Research and Development (IJTSRD)	Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Back Propagation Algorithm (Neural Networks)	Hair removal, shading removal, glare removal, segmentation, feature extraction (color, shape, size, texture)	Quick detection time aids technicians in improving diagnostic skills. Three-phase model (data collection, model design, prediction) incorporating AI algorithms like CNN and SVM. Achieves 85% accuracy due to amalgamation with image processing tools.	Cancer often diagnosed late, leading to less effective treatments. Segmentation is crucial; supervised segmentation based on parameters (shapes, sizes, colors, skin types, textures) is beneficial but challenging.
17.	A Smartphone-Based Skin Disease Classification Using MobileNet CNN	2019	Jessica Velasco, Cherry Pascion, Jean Wilmar Alberio, Jonathan Apuang, John Stephen Cruz, Mark Angelo Gomez, Benjamin Jr. Molina, Lyndon	International Journal of Advanced Trends in Computer Science and Engineering	MobileNet model using transfer learning for skin disease classification on an Android application Different sampling methods and preprocessing of input	Learning rate: 0.0001 Activation: Softmax Loss: Categorical crossentropy Optimizer: Adam Epoch: 30 Data augmentation parameters: Rescale (1./255), Rotation	Using undersampling method and default preprocessing achieved 84.28% accuracy on the test dataset. Using the imbalanced dataset and default preprocessing achieved 93.6%	The system misclassified most of the psoriasis test images as acne and pityriasis rosea. Despite the initial misclassification, accuracy for psoriasis increased from 75% to 80%. The model's rank-1 accuracy

			Tuala, August Thio-ac, Romeo Jr. Jorda		data were explored. Fine-tuning the parameters of the pretrained MobileNet model.	range (40), Width shift range (0.2), Height shift range (0.2), Shear range (0.2), Zoom range (0.2), Horizontal flip (True), Fill mode (Nearest)	accuracy. Oversampling method achieved 91.8% accuracy. Oversampling combined with data augmentation achieved 94.4% accuracy. Exploring different sampling techniques and preprocessing methods can enhance model accuracy. Oversampling and data augmentation generated the most accurate results in the study.	improved to 94.4%.
18.	Dermatologist Level Dermoscopy Skin Cancer Classification Using Different Deep Learning Convolutional Neural Networks Algorithms	Not mentioned explicitly	Amirreza Rezvantalab, Habib Safigholi, Somayeh Karimijeshni	Not mentioned explicitly	DenseNet 201, ResNet 152, Inception v3, InceptionResNet v2	Dataset: 10135 dermoscopy skin images from HAM10000 (10015) and PH2 (120)Diagnostic Categories: Melanoma, melanocytic nevi, basal cell carcinoma, benign keratosis, actinic keratosis, intraepithelial carcinoma, dermatofibro	ResNet 152 achieved the best ROC AUC values for melanoma (94.40%) and DenseNet 201 for basal cell carcinoma (99.30%). DenseNet 201 had the highest macro (98.16%) and micro (98.79%) averaged AUC values for overall classification.	Insufficient data and lack of diversity in skin cancer classes are major problems. Many approaches rely heavily on 'man-made' segmentation criteria, which is a limitation..

						ma, vascular lesions, atypical nevi Pre-trained architectures : DenseNet 201, ResNet 152, Inception v3, InceptionResNet v2 ROC AUC values for melanoma and basal cell carcinoma: 94.40% (ResNet 152) and 99.30% (DenseNet 201) Macro and micro averaged AUC values for DenseNet 201: 98.16%, 98.79%		
19.	Automated deep learning approach for classification of malignant melanoma and benign skin lesions	2022	Wessam Salma, Ahmed S. Eltrass	Multimedia Tools and Applications	Novel automated Computer-Aided Diagnosis (CAD) system using various pretrained convolutional neural networks (CNNs) including VGG-16, ResNet50, ResNetX, InceptionV3, and MobileNet. Combined with Support	Average 5-fold cross-validation results, data augmentation strategies, various evaluation metrics (area under the ROC curve, accuracy, sensitivity, precision, F1-score, and computational time).	The proposed framework can aid medical practitioners in classifying different skin lesions. Experimental results show superior performance of the proposed approach over recent techniques, with metrics such as: Area under the ROC curve: 99.52% Accuracy: 99.87%	Despite high performance, there are limitations that need future investigation. The number of pre-trained CNN architectures can be increased to include more recent and advanced models. Extracting comprehensive features like ABCD features may have practical limitations, such as misclassifying melanoma with homogeneous

					Vector Machine (SVM) for final classification.		Sensitivity: 98.87% Precision: 98.77% F1-score: 97.83% Consumed time: 3.2 seconds Data augmentation positively impacts diagnosis performance.	color and regular shape.
20.	Accurate skin cancer diagnosis based on convolutional neural networks	2022	Amal G. Diab, Nehal Fayez, Mervat Mohamed El-Seddek	Indonesian Journal of Electrical Engineering and Computer Science	Convolutional Neural Networks (CNN) using GoogleNet, ResNet-50, AlexNet, and VGG19, combined with Support Vector Machine (SVM) classifier.	Datasets: ISIC 2019, CPTAC-CM Models: GoogleNet, ResNet-50, AlexNet, VGG19 Training Configuration: Learning rate: 10^-4 Mini-batch size: 128 Number of epochs: 20 Maximum iterations: 606 (AlexNet), 642 (ResNet-50), 612 (GoogleNet), 600 (VGG19)	High accuracy: 99.8% for ISIC database, 99.9% for CPTAC-CM database. Automated optimal approach for isolating the region of interest (RoI) in skin lesions.	Requires massive data for building new CNN models to avoid overfitting. High computational costs, especially during the training process. Similarity in color and texture among different types of skin lesions can lead to misclassification.
21.	Untangling Classification Methods for Melanoma Skin Cancer	2022	Ayushi Kumar and Avimanyou Vatsa	Frontiers in Big Data	Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and XG-Boost	Loss, accuracy, precision, recall, F1 score, and ROC	CNN's VGG16 architecture had an accuracy of 89.6%, the best among the seven architectures tested. RNN's bidirectional architecture	The F1 score of CNN's VGG16 was lower due to data imbalance, despite high accuracy. RNN required transformation of input data, leading to potential loss of

							showed an accuracy of 95.96%. XG-Boost achieved the highest accuracy of 97.22%.	important features. XG-Boost, while having high accuracy, may not generalize well due to limited dataset.
22.	Melanoma Classification Using a Novel Deep Convolutional Neural Network with Dermoscopic Images	2022	Ranpreet Kaur, Hamid GholamHosseini, Roopak Sinha, Maria Lindén	Sensors	Deep Convolutional Neural Network (DCNN)	Accuracy, precision, recall, specificity, F1-score	LCNet model achieved ACC, PRE, and REC of 81.41%, 81.88%, and 81.30% for MEL vs. BEN on ISIC 2016 dataset. On ISIC 2017, it achieved 88.23% ACC, 78.55% PRE, and 87.86% REC for MEL vs. NV and SK. Achieved 90.42% ACC, 90.48% PRE, and 90.39% REC on ISIC 2020 and 76.0%, 67.8%, and 75.3% on PH2 dataset.	Skin lesion classes in datasets are highly imbalanced (e.g., NV vs. SK and MEL in ISIC 2017, BEN vs. MEL in ISIC 2020). Lesions often contain noisy artefacts such as hairlines, gel bubbles, and ruler marks. High intra-class differences and inter-class similarities make distinguishing lesion types challenging.
23.	A Comprehensive Evaluation and Benchmarking of Convolutional Neural Networks for Melanoma Diagnosis	2021	Saeed Alzahrani, Baidaa Al-Bander, Waleed Al-Nuaimy	Cancers	Multi-Criteria Decision Making (MCDM) integrating entropy and PROMETHEE methods	Accuracy, Classification error, Precision, Sensitivity, Specificity, F1-score, False-positive rate, False-negative rate, Matthews correlation coefficient (MCC), Number of parameters	Provides a powerful linkage between multi-criteria decision-making techniques and objective performance evaluation criteria. Helps rank learning models based on multiple conflicting criteria and select the	Despite progress in benchmarking models for melanoma diagnosis from dermoscopy images, there is still room for improvement. Future work aims to: Study the effect of model selection considering different criteria. Train models under several transfer learning

							optimal model in the case study. Comprehensive evaluation of 19 convolutional neural network models with a two-class classifier. Models are trained and evaluated on a dataset of 991 dermoscopic images considering 10 performance evaluation metrics.	scenarios and data augmentation strategies. Explore the impact of various optimization schemes. Test various class balancing and weighting techniques. Train models on multiple datasets to understand the effect of variation among datasets.
24.	Robust skin diseases detection and classification using deep neural networkS	2018	Saad Albawi, Yasir Amer Abbas, Yasser Almadanie	International Journal of Engineering & Technology	Convolutional Neural Network (CNN)	Accuracy: 96.768% Specificity: Not specified Sensitivity: Not specified	Achieved a classification accuracy of 96.768% for skin diseases. Outperformed state-of-the-art techniques in results.	Risky to claim AI superiority over human doctors based on this study. Segmentation is crucial; supervised segmentation considers parameters like shapes, sizes, colors, skin types, and textures.
25.	The Development of a Skin Cancer Classification System for Pigmented Skin Lesions	2020	Shunichi Jinnai, Naoya Yamazaki, Yuichiro Hirano, Yohei Sugawara, Yuichiro Ohe, Ryuji Hamamoto	Biomolecules	Faster Region-based Convolutional Neural Network (FRCNN)	Accuracy (six classes): 86.2% Accuracy (two classes): 91.5% Sensitivity: 83.3% Specificity: 94.5% False Positive	The accuracy of the system was better than that of dermatologists. It successfully detected not only malignant melanoma, but also basal	It is risky to judge that artificial intelligence (AI) is superior to human medical doctors based on this study. FRCNN has been reported to have difficulty identifying

	Using Deep Learning					Rate: 5.5% Positive Predictive Value: 84.7%	cell carcinoma. The classification accuracy of FRCNN was better than that of the dermatologists.	objects from low-resolution images, due to its weak capacity to identify local texture.

"Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM (2021)" This study, authored by Parvathaneni Naga Srinivasu et al., published in Sensors, utilizes MobileNet V2 and Long Short-Term Memory (LSTM) algorithms for the classification of skin diseases. The methodology and performance evaluation sections discuss various parameters, including learning rate, batch size, and number of epochs. The advantages of this approach include its efficiency in maintaining stateful information for precise predictions, its compatibility with lightweight computational devices, and its superior accuracy compared to other state-of-the-art models with minimal computational effort. However, a notable disadvantage is the significant computational efforts required for GLCM, and the characteristics are not invariant to rotation and texture changes.

"Skin Cancer Disease Detection Using Transfer Learning Technique (2022)" Javed Rashid et al., in their paper published in Applied Sciences, explore the use of MobileNetV2 for melanoma classification through transfer learning. They discuss parameters such as learning rate, batch size, number of epochs, and augmentation techniques. The advantages highlighted include the technique's superior accuracy and computational cost efficiency, with MobileNetV2 optimizing execution speed and memory consumption. However, the study points out the scarcity of high-quality medical imaging datasets for training and the tendency of CNNs with simple architecture to overfit limited training datasets.

"Primary Vulval Melanoma and Genital Lichen Sclerosus (2024)" *Evanthia* Mastoraki et al. focus on a clinical review and literature analysis in their study published in Skin Health and Disease. They examine histopathological features, clinical records, and literature data. The study suggests a potential causative relationship between genital lichen sclerosus (LS) and vulval melanoma, with implications for early diagnosis, management, and follow-up of genital LS. However, the study is limited by its size, the retrospective collection of data, and the lack of clinical photographs, which might distort histopathology findings.

"Skin Cancer Detection Using Image Processing (2017)" In this study by Uzma Bano Ansari and Tanuja Sarode, published in the International Research Journal of Engineering and Technology (IRJET), image processing and Support Vector Machine (SVM) algorithms are used. Parameters include grayscale conversion, noise removal, image enhancement, segmentation using maximum entropy thresholding, and feature extraction using GLCM. The advantages include early detection of skin cancer, preventing unnecessary excisions of harmless moles and lesions, with an accuracy of 95%. However, the study is limited by the availability of high-quality images for processing and the risk of misclassification due to variations in image quality and preprocessing techniques.

"Skin Lesion Classification Using CNN With Novel Regularizer (2019)" Authored by M. A. Albahar and published in IEEE Access, this paper employs a CNN with a novel regularizer. The parameters include a regularizer based on the standard deviation of the weight matrix, convolution layers, and ReLU activation. The proposed model achieved a maximum average accuracy of 97.49%, with lesser computational complexity and better generalization capability. However, it is not suitable for feature selection or reduction, and choosing a suitable value of λ is computationally expensive and time-intensive.

"Skin Lesion Detection Using Hand-Crafted and DL-Based Features Fusion and LSTM (2022)" Rabbia Mahum and Suliman Aladhadh, in their paper published in Diagnostics, combine Local Binary Patterns (LBP), Inception V3, and LSTM algorithms. Parameters include Gaussian Filtering for noise removal, LBP for feature extraction, and the Adam optimizer for learning rate adjustment. The model achieved 99.4% accuracy, 98.7% precision, 98.66% recall, and a 98% F-score, using a small number of training samples due to transfer learning. However, automated methods based on hand-crafted feature extraction may fail to detect skin cancers at an early stage when tested on unseen data.

"Ensemble-Based CNN Models for Melanoma Detection (2019)" Eduardo Perez and Sebastian Ventura's study, published in Neural Computing and Applications, utilizes an ensemble of CNN models, including DenseNet, MobileNet, and InceptionV3. Parameters involve various optimizers like SGD, RMSprop, Adam, and Nadam. The models performed best on segmented data, with MobileNet, DenseNet, and InceptionV3 being the top performers. However, the UDA-2 dataset was challenging, and the models achieved only 44% MCC on average, with a risk of overfitting on small datasets.

"Skin Cancer Detection System Project (2024)" Riya Jaiswal et al., in their study published in the International Journal of Research Publication and Reviews, use CNN and K-Nearest Neighbors (KNN) algorithms. Parameters include image preprocessing, segmentation, feature extraction, and CNN model training. The proposed CNN model performs well in imaging for cancer screening and early diagnosis, offering a user-friendly GUI interface. However, the complexity of the dataset, involving approximately 25000 images in the HAM10000 dataset, limits the study to 800 images, indicating it should not completely replace medical personnel-based diagnosis.

"Skin Disease Prediction (2023)" Authored by D. Jena et al. and published in the International Journal for Multidisciplinary Research (IJFMR), this study uses CNN for image classification and Softmax for multi-class classification. Parameters include filters for specific image features, ReLU activation function, pooling layers, fully connected layers, and the Softmax function. The models offer tailored treatment suggestions using patient data, with advancements in artificial intelligence enhancing the accuracy and dependability of the recommendations. Nevertheless, obstacles arise from the necessity of establishing consistent datasets and distinguishing between various skin conditions.

“Automatic Classification of Melanoma Skin Cancer with Deep Convolutional Neural Networks (2019)” Khalil Aljohani and Turki Turki's study, published in AI, employs various CNN architectures like DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, and VGG19. Parameters involve a dataset of 7146 images from the ISIC dataset and image size of 224 × 224 pixels. The advantages include facilitating accurate and swift decision-making in medical diagnostics, overcoming human limitations. However, it requires extensive data for training, costly high-quality hardware like GPUs, and is susceptible to noise in medical images.

“Discriminative Feature Learning for Skin Disease Classification Using Deep Convolutional Neural Network (2020)” This study by Belal Ahmad et al., published in IEEE Access, employs deep CNNs, fine-tuned ResNet152, and InceptionResNet-V2 with a triplet loss function. Parameters include fine-tuning layers, triplet loss function, 128-D embeddings in Euclidean space, learning rate, and momentum. The model outperforms state-of-the-art methods, enhancing effectiveness. However, it has slower convergence due to inactive triplets during training and risks generating indecisive results in small mini-batches.

“Classification of Melanoma Skin Cancer using Convolutional Neural Network (2019)” Authored by Rina Refianti et al. and published in the International Journal of Advanced Computer Science and Applications (IJACSA), this study uses CNN with LeNet-5 architecture. Parameters include the LeNet-5 architecture, training with 176 images, and 100 epochs. The advantages include using deep learning technology, achieving 93% training success, and 100% testing success with varying datasets. However, the study's reliance on non-public datasets limits reproducibility and comparability with other methods.

“Convolutional Neural Network (CNN) for Automatic Skin Cancer Classification System (2020)” Yunendah Nur Fu’adah et al., in their study published in IOP Conference Series: Materials Science and Engineering, use CNNs. Parameters include layers like input, convolution, activation, pooling, and fully connected, along with optimizers like SGD, RMSprop, Adam, and Nadam. The model achieved 99% accuracy using the Adam optimizer, recognizing various skin conditions. However, models using other optimizers showed overfitting, and there were errors in detecting specific conditions.

“Intelligent System for Skin Disease Prediction using Machine Learning (2021)” This study by Ahmed A. Elngar et al., published in the Journal of Physics: Conference Series, uses a CNN combined with SVM (CNN-SVM-MAA). Parameters include convolutional layers, ReLU activation, pooling layers, fully connected layers, and the Softmax function. The system facilitates early disease identification and treatment, utilizing modified pre-trained CNN and SVM algorithms. However, challenges include the need for standardized datasets and difficulty in distinguishing similar skin diseases.

"A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks (2019)" Samuel Akyeramfo-Sam et al., in their study published in the International Journal of Information Technology and Computer Science (IJITCS), use CNNs for a web-based diagnosis system. Parameters include convolutional layers, ReLU activation, pooling layers, fully connected layers, and the Softmax function. The system enhances accuracy and speed in dermatological diagnosis, providing a real-time learning platform. However, reliance on manual visual clues and limited sample data from medical centers pose challenges.

"Melanoma Skin Cancer Detection using Image Processing and Machine (2019)" Vijayalakshmi M M's study, published in the International Journal of Trend in Scientific Research and Development (IJTSRD), uses CNN, SVM, and Back Propagation Algorithm. Parameters include hair removal, shading removal, glare removal, segmentation, and feature extraction. The model aids in quick detection, improving diagnostic skills with 85% accuracy. However, late cancer diagnosis and the challenge of supervised segmentation based on parameters are noted limitations.

"A Smartphone-Based Skin Disease Classification Using MobileNet CNN (2019)" Jessica Velasco et al., in their study published in the International Journal of Advanced Trends in Computer Science and Engineering, use the MobileNet model for skin disease classification on an Android application. Parameters include learning rate, activation, loss, optimizer, epochs, and data augmentation techniques. The study achieved high accuracy using oversampling and data augmentation. However, the system misclassified some test images, indicating the need for improvement.

"Dermatologist Level Dermoscopy Skin Cancer Classification Using Different Deep Learning Convolutional Neural Networks Algorithms" This study by Amirreza Rezvantalab et al. employs various CNN architectures like DenseNet 201, ResNet 152, Inception v3, and InceptionResNet v2. Parameters include the HAM10000 and PH2 datasets, achieving high ROC AUC values for melanoma and basal cell carcinoma. However, the study highlights issues with data diversity and reliance on man-made segmentation criteria.

"Automated deep learning approach for classification of malignant melanoma and benign skin lesions (2022)" Authored by Wessam Salma and Ahmed S. Eltrass, published in Multimedia Tools and Applications, this study uses various pretrained CNNs combined with SVM for final classification. Parameters encompass cross-validation outcomes, data augmentation techniques, and diverse evaluation metrics. The framework exhibits outstanding performance, achieving high accuracy and providing rapid diagnosis. Nevertheless, there are certain constraints, such as the requirement for more sophisticated models and comprehensive feature extraction.

"Accurate skin cancer diagnosis based on convolutional neural networks (2022)" Amal G. Diab et al., in their study published in the Indonesian Journal of Electrical Engineering and Computer Science, use CNNs combined with SVM classifiers. Parameters include datasets, models, and training configurations. The system achieved high accuracy and facilitated optimal RoI isolation. However, it requires massive data and incurs high computational costs, with challenges in distinguishing similar skin lesions.

"Untangling Classification Methods for Melanoma Skin Cancer (2022)" This study by Ayushi Kumar and Avimanyou Vatsa, published in Frontiers in Big Data, uses CNN, RNN, and XG-Boost algorithms. Parameters include loss, accuracy, precision, recall, F1 score, and ROC. XG-Boost achieved the highest accuracy, followed by RNN and CNN. However, the F1 score for CNN was lower due to data imbalance, and RNN required data transformation, potentially losing important features.

"Melanoma Classification Using a Novel Deep Convolutional Neural Network with Dermoscopic Images (2022)" Authored by Ranpreet Kaur et al., published in Sensors, this study uses a deep CNN model. Parameters include accuracy, precision, recall, specificity, and F1-score. The LCNet model achieved high performance on multiple datasets. However, the study faces challenges with imbalanced skin lesion classes, noisy artifacts, and distinguishing lesion types.

"A Comprehensive Evaluation and Benchmarking of Convolutional Neural Networks for Melanoma Diagnosis (2021)" Saeed Alzahrani et al., in their study published in Cancers, use MCDM integrating entropy and PROMETHEE methods. Parameters include accuracy, classification error, precision, sensitivity, specificity, F1-score, false-positive rate, false-negative rate, MCC, and the number of parameters. The study provides a comprehensive evaluation of 19 CNN models, but there is room for improvement in model selection and benchmarking.

"Robust skin diseases detection and classification using deep neural networks (2018)" This study by Saad Albawi et al., published in the International Journal of Engineering & Technology, uses CNNs. Parameters include accuracy, achieving a classification accuracy of 96.768%. However, the study highlights the risk of claiming AI superiority over human doctors and supervised segmentation based on various parameters.

"The Development of a Skin Cancer Classification System for Pigmented Skin Lesions Using Deep Learning (2020)" Authored by Shunichi Jinnai et al., published in Biomolecules, this study uses Faster Region-based CNN (FRCNN). Parameters include accuracy, sensitivity, specificity, false positive rate, and positive predictive value. The system achieved better accuracy than dermatologists in detecting malignant melanoma and basal cell carcinoma. However, the study notes the difficulty of identifying objects from low-resolution images with FRCNN.

4. Technologies Used

The proposed "Skin Health Prediction App" leverages a variety of advanced technologies to ensure accurate skin disease identification and provide a user-friendly experience. Below are the key technologies utilized in the project, with detailed descriptions of their roles and benefits:

4.1. Machine Learning (TensorFlow)

Tensorflow, a robust open-source machine learning framework created by Google, is employed to construct and deploy a convolutional neural network (cnn) model for the classification of skin diseases. This model analyzes user-submitted images to accurately identify various skin conditions. TensorFlow's flexibility and scalability make it ideal for handling complex image recognition tasks. It supports both training and inference on a range of hardware configurations, from CPUs to GPUs and TPUs, allowing for efficient processing of large datasets and real-time predictions. The use of TensorFlow also benefits from its high-level APIs, such as Keras, which simplify the creation and training of machine learning models, and its visualization tool, TensorBoard, which helps in tracking and visualizing the model training process.

4.2. Mobile App Development (Android Studio)

Android Studio is employed to develop a user-friendly mobile application interface. This interface allows users to easily upload images, receive diagnostic results, and access additional features such as dermatologist recommendations and prescription suggestions. The Layout Editor in Android Studio supports drag-and-drop functionality, making it easier to design intuitive and visually appealing interfaces. Additionally, the built-in emulator allows for extensive testing across different Android devices and versions, ensuring compatibility and smooth user experiences.

4.3. Database Management (Firebase)

Firebase acts as the repository for storing user data, encompassing uploaded images, categorized skin conditions, and recommended treatments. Firebase provides real-time data synchronization and offline support, guaranteeing a smooth experience for users even when they are not connected to the internet. Its strong security measures guarantee that user data remains secure and can only be accessed by authorized individuals. Firebase's real-time database feature enables immediate updates, which is essential for ensuring accurate and current information for all users. Additionally, firebase's authentication services offer secure login options, such as email/password, phone, and social media logins, which improve user security and convenience.

4.4 Model Training and Development (Google Colab)

Google Colab, a cloud-based Jupyter notebook surroundings, is employed to broaden and teach the CNN version. Google Colab presents access to effective GPUs and TPUs without charge, making it a super platform for training deep studying models. It supports real-time collaboration and integrates seamlessly with Google drive, allowing green information control and sharing. The cloud-based totally nature of Google Colab allows for scalable computational resources, which can be important for dealing with the in depth education procedures required for deep learning fashions. This platform additionally helps the usage of numerous Python libraries, improving the development and experimentation manner.

4.5. Image Processing

Various image processing techniques are applied to preprocess and analyze the skin images submitted by users. These techniques include steps such as noise reduction, normalization, enhancement, and feature extraction, which are essential for preparing the images for accurate classification by the CNN model. Techniques like histogram equalization, edge detection, and segmentation improve the quality and relevance of the images, ensuring that the model receives high-quality input data. Those preprocessing steps help in improving the functions of the snap shots which are crucial for the model to research and make accurate predictions.

4.6. Programming Languages (Python and Java)

Python, a widely used programming language in AI and machine learning, is utilized for implementing the CNN algorithms and developing various components of the project management tool. Python's simplicity and extensive libraries make it an ideal choice for machine learning projects. Libraries such as TensorFlow, Keras, OpenCV, and Scikit-learn provide powerful tools for building and deploying machine learning models. Python's versatility allows for rapid prototyping as well as production-level deployment, making it a cornerstone of the project's development process. Java, often used for building large-scale, enterprise-level applications, is employed for certain backend components, data processing tasks, or integration with other systems. The use of Java ensures that the backend processes are scalable and maintainable, capable of handling the complex interactions between the app.

4.7. Integration and User Experience

By integrating these technologies, the "Skin Health Prediction App" aims to provide users with a convenient and reliable tool for early skin disease detection, enhancing their skin health effectively. The combination of machine learning, mobile app development, cloud storage, and advanced image processing techniques ensures a robust and user-friendly application that meets the needs of users and healthcare providers alike. The synergy of these technologies not only improves the accuracy and efficiency of skin disease diagnosis but also ensures that the app is scalable, comfortable, and handy, imparting a comprehensive answer for pores and skin fitness.

5. METHODOLOGY

5.1. Proposed System

The proposed "Skin Health Prediction App" aims to revolutionize skin disease diagnosis and treatment by leveraging cutting-edge technologies. The device includes numerous additives operating collectively to provide correct and timely pores and skin situation evaluation.

5.1.1. Mobile Application

Developed using Android Studio, the mobile application allows users to easily upload images of their skin issues. The user interface is designed to be intuitive, making the process of capturing and uploading images straightforward. This user-centric design ensures that individuals, regardless of their technical proficiency, can navigate the app with ease, enabling them to quickly receive insights into their skin health. The application also includes interactive features such as guided image capture instructions to ensure high-quality uploads, and real-time feedback on image quality to improve diagnostic accuracy.

5.1.2. CNN Model (TensorFlow)

The center capability of the app is powered through a Convolutional Neural network (CNN) version constructed the use of TensorFlow. This version is trained on a numerous dataset of pores and skin situation pictures to make certain accurate class. The version is deployed the use of Google Colab, allowing real-time processing of consumer-uploaded snap shots. TensorFlow's powerful abilities permit the version to handle a extensive variety of skin conditions, making sure high accuracy and reliability within the diagnostic procedure. The model leverages superior deep mastering strategies such as transfer mastering and facts augmentation to beautify its performance and robustness towards versions in image pleasant and lighting situations.

5.1.3. Image Analysis and Classification

Once an image is uploaded, the CNN model analyzes it and categorizes the skin condition. The app then provides users with detailed information about the identified condition, helping them understand their skin health better. This feature not only aids in immediate self-assessment but also educates users about potential skin issues, empowering them with knowledge and promoting proactive skin care. Detailed analysis includes possible symptoms, common treatments, and preventive measures for each identified condition.

5.1.4. Dermatologist and Clinic Recommendations

To ensure users receive appropriate medical advice, the app suggests nearby dermatologists or skin clinics for further evaluation. This feature helps diagnosis and professional medical consultation. By integrating geolocation services, the app can provide personalized recommendations, easy for users to find and book appointments with dermatologists and clinics in their vicinity. The app may also include a feature to book virtual consultations, allowing users to get professional advice without leaving their homes.

5.1.5. Prescription Alternatives

For common skin problems, the app offers simple prescription alternatives, providing users with accessible treatment options. This feature is particularly beneficial for individuals who may not have immediate access to a dermatologist. The app recommends over-the-counter solutions that are effective and easy to obtain, ensuring users can begin treatment promptly while they seek professional advice. The app provides information on the effectiveness, usage instructions, and possible side effects of each recommended product, ensuring that users can make decisions on treatment options.

5.1.6. Firebase Database

Firebase is used to securely store user data, including images, categorized conditions, and treatment suggestions. Its real-time data syncing and offline support capabilities ensure that users can access their data anytime, anywhere. This seamless data management system enhances the user experience by providing consistent access to personal health records, even in areas with limited internet connectivity. Firebase’s robust infrastructure supports large-scale data operations, ensuring that the app remains responsive and reliable under heavy usage.

5.1.7. Privacy and Security

Robust privacy and security measures are implemented to protect user data, complying with relevant regulations such as GDPR and HIPAA. The app educates users on the importance of consulting a doctor for a proper diagnosis and treatment plan, ensuring they understand the app's role as a supportive tool rather than a replacement. User data is anonymized and securely stored, and access controls are in place to prevent unauthorized access, ensuring that users' privacy is always maintained.

By integrating these components, the "Skin Health Prediction App" provides a comprehensive solution for early skin disease detection and management, promoting better skin health and accessibility to professional medical advice. The app's holistic approach combines advanced technology with user-friendly features, ensuring that users receive accurate, timely, and actionable insights into their skin health. This integration enhances the overall user experience, making the app a valuable tool for both users and healthcare providers.

5.2. Existing System

5.2.1. Traditional Diagnosis Methods

Traditional diagnosis of skin diseases primarily involves physical consultations with dermatologists. Patients visit clinics or hospitals where dermatologists perform visual inspections and may use tools like dermatoscopes for a closer examination of the skin. In more serious cases, biopsies or lab tests are conducted to confirm diagnoses. This method leverages the expertise of dermatologists, who have extensive training and experience in diagnosing and treating skin conditions. Physical consultations allow for comprehensive evaluations, including palpation and consideration of patient history. However, this approach has significant drawbacks. Access to dermatologists can be limited, especially in rural or underserved areas.

The process of scheduling and attending appointments can take more time, and the cost of in-person consultations and follow-up visits can be prohibitive for uninsured or underinsured individuals. Additionally, the waiting time for appointments and test results in late diagnosis and treatment.

5.2.2. Self-Diagnosis and Online Information

Apart from immediate access to professional healthcare, many individuals turn to self-diagnosis using online resources. These include websites, forums, and mobile apps that provide general information on skin conditions. Such platforms often feature symptom checkers and image comparisons to help users identify potential skin issues. The main advantage of these resources is their convenience; they are easily accessible from home at any time and are generally free or low-cost. However, the major downside is the high risk of misdiagnosis. Without a professional evaluation, users can misinterpret their symptoms, leading to incorrect self-diagnosis and potentially harmful treatments. These resources offer limited personalization, often providing generic advice that does not take into account individual medical histories or specific symptoms. Relying on self-diagnosis can result in the worsening of conditions or missed serious diagnoses.

5.2.3. Existing Technological Solutions

There are rising technologies and apps that intention to improve pores and skin disorder analysis thru using AI and gadget studying. those consist of cell apps and online platforms that make use of photo reputation to discover skin conditions. these technological solutions offer numerous benefits, including velocity and accessibility. customers can quick acquire evaluation and feedback, that is extensively faster as compared to conventional strategies. these answers may be used anywhere with a web connection, making them greater reachable to a much wider target market and normally greater fee-powerful than repeated visits to dermatologists. but, these solutions additionally face vast demanding situations. The accuracy of those apps and structures varies, and they will no longer continually be reliable. There are also critical worries regarding facts privacy, as coping with touchy fitness data requires sturdy security features. Many current apps consciousness on a slender range of situations, limiting their diagnostic abilities. moreover, these solutions frequently lack integration with healthcare structures, decreasing their utility in supplying ongoing affected person care and expert session.

6. Database Architecture

6.1. Cloud-Based Storage

The cloud-based storage solution is specifically designed to securely store user data and medical images in the cloud. This guarantees that the data can be easily expanded and consistently available whenever needed.

Functionality:

a) Cloud storage has the capability to expand and accommodate the increasing volume of data as more users upload their images and information. This is crucial for managing a large number of users and handling large amounts of data without affecting performance.
b) Cloud providers guarantee high availability and redundancy, ensuring that data is always accessible and not at risk of being lost due to hardware failures or other problems. This reliability is crucial for building user trust and ensuring uninterrupted access to their data.
c) The cloud storage ensures the security of user data through encryption, access control, and regular audits, safeguarding it from unauthorized access and breaches. Adhering to regulations such as gdpr and hipaa guarantees that the app complies with legal requirements for safeguarding user data.

6.2. Machine Learning Models

The app employs cutting-edge artificial intelligence algorithms, particularly convolutional neural networks (cnns), to analyze skin images and generate disease predictions.

Functionality:

a) Image analysis: the machine learning models are trained on a diverse dataset of skin condition images. They possess the ability to categorize different skin conditions by recognizing patterns and characteristics in the images.
b) Disease prediction: after an image is uploaded, the model analyzes it and predicts the skin condition. This process involves multiple steps, such as image preprocessing, feature extraction, and classification.
c) Continuous learning: the models are constantly updated and retrained with fresh data to enhance their accuracy and adaptability to various skin conditions. This continuous learning process guarantees that the app remains efficient and dependable as time goes on.

6.3. User Interface

The mobile app boasts a user-friendly interface created using android studio. This interface enables users to effortlessly upload images and view the results in a seamless manner.

Functionality:

a) The interface of the app is designed to be user-friendly, ensuring that users can easily navigate through the app, capture images, and upload them for analysis. The app provides clear and straightforward instructions, along with a user-friendly interface, ensuring that users can navigate and interact with it without any confusion.

b) The app enables seamless image upload, making it easy for users to capture and upload their skin condition images for analysis without any hassle. This streamlines the process for users, making their experience more enjoyable and efficient.

c) The app presents the analysis results in a user-friendly manner, making it simple for users to comprehend. Users are provided with comprehensive information about the specific skin condition, potential treatment options, and suggestions for seeking professional advice from dermatologists. This guarantees that users can make well-informed choices based on the app's analysis.

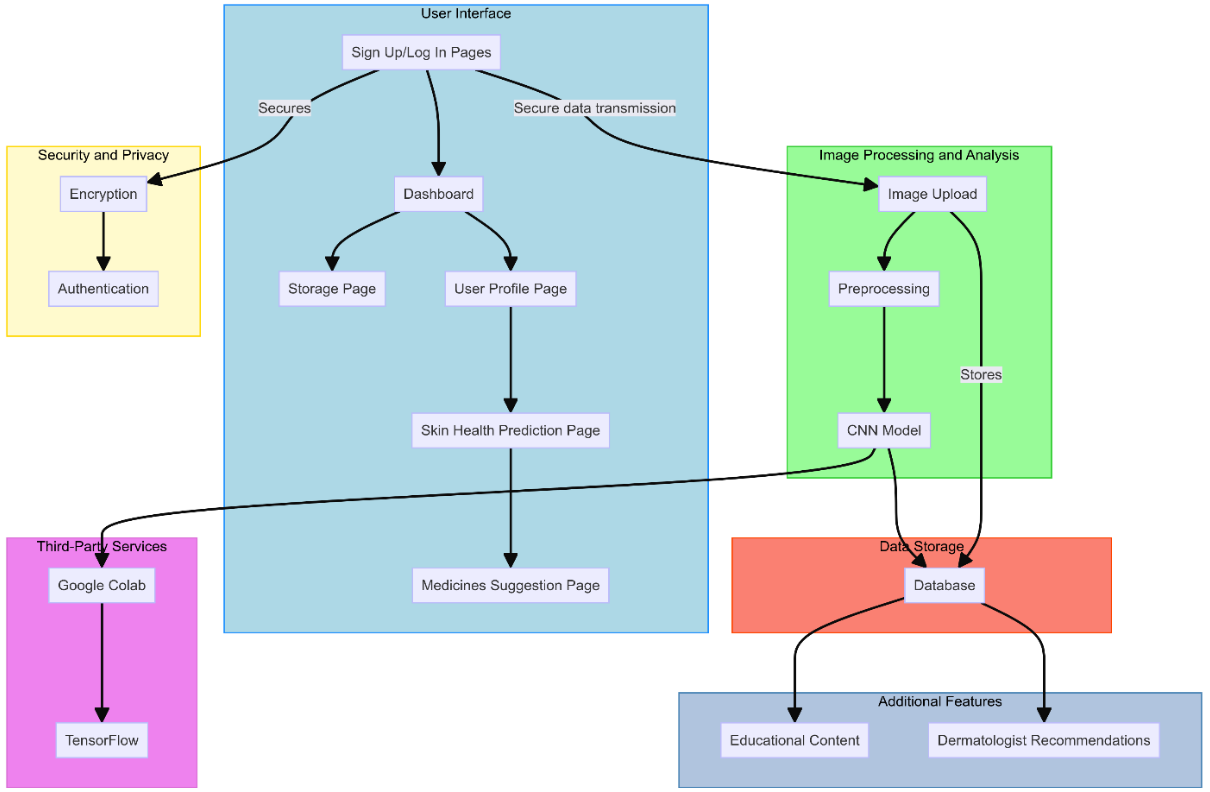

Fig. Architecture Diagram

7. Machine Learning Models

The machine learning models used in the Skin Health Prediction App are critical for accurately identifying and categorizing various skin conditions based on user-submitted images. This process involves three main stages: Data Collection, Model Training, and Deployment. Below is an in-depth explanation of each stage:

7. 1. Data Collection

Curating a Diverse Dataset of Skin Condition Images:

a) **Objective**: The first step in developing a reliable machine learning model is to gather a large and diverse set of images that represent skin conditions.

b) **Sources**: These images can be sourced from publicly available medical image databases, dermatological research publications, and clinical datasets. Collaboration with dermatologists and medical institutions can also provide access to high-quality, labeled images.

c) **Diversity**: The dataset includes images of different skin types, ages, genders, and various environmental conditions. This diversity helps the model generalize better and perform accurately across different populations.

d) **Labeling**: Each image is accurately labeled with the corresponding skin condition. This labeling is typically done by medical experts to ensure correctness and reliability.

7.2. Model Training

Designing and Training the CNN Model Using TensorFlow:

a) **Model Design**: a convolutional neural network (cnn) is chosen for its effectiveness in image recognition tasks. CNN architecture typically comprises several layers, such as convolutional layers, pooling layers, and fully connected layers.
   i. **convolutional layers:** these layers apply filters to the input image to detect features such as edges, textures, and shapes.
   ii. **pooling layers:** these layers help to simplify the data, keeping the most important information and making the computations easier.**Fully Connected Layers**: These layers interpret the extracted features and make the final classification decision.

b) **Training Process**: The training process involves feeding the labeled images into the CNN model. The model learns to find patterns and insights associated with each skin condition through a process called backpropagation.

i) **Optimization**: Techniques like gradient descent are used to minimize the error between the model's predictions and the actual labels.

ii) **Evaluation**: The model's performance is evaluated using metrics such as accuracy, precision, recall, and the F1-score. These metrics help in assessing model performance and identifying areas for improvement.

iii) **Hyperparameter Tuning**: Parameters such as learning rate, batch size, and the number of epochs are tuned to achieve the best performance. This process involves experimenting with different values to find the optimal configuration.

7.3. Deployment

Deploying the Trained CNN Model on Google Colab for Real-Time Analysis:

a) **Objective**: After the model is trained and validated, it needs to be deployed in such where it allows real-time analysis of user-submitted images.

b) **Google Colab**: Google Colab is chosen as the deployment environment due to its powerful computational resources, easy to use and integration with TensorFlow.

i) **Integration**: The trained CNN model is integrated into a cloud-based Jupyter notebook environment on Google Colab. This allows the model to process images uploaded by users through the mobile app.

ii) **Real-Time Processing**: When a user uploads an image, the app sends the image to the Google Colab environment where the model processes it and returns the classification result. This process is designed to be fast and efficient, providing users with instant feedback.

iii) **Scalability**: Google Colab can handle multiple concurrent requests, making it suitable for real-time analysis. It also allows for easy updates and retraining of the model as new data becomes available.

8. Implementation

The implementation of the Skin Health Prediction App involves several key steps, from image upload to processing and result display. This detailed explanation will cover each step, outlining the processes and technologies used.

8.1. Image Upload

The first step in using the Skin Health Prediction App is uploading an image of the skin condition. This process is designed to be user-friendly and secure.

User Interface:

a. **Capture or Select Image**: Users can either capture a new image using their smartphone's camera or select an existing image from their gallery. The app provides clear instructions and an intuitive interface to guide users through this process. The camera interface might include features such as autofocus, flash control, and a countdown timer to ensure the image is captured correctly.

b. **Image Quality**: The accurate analysis, the app may provide guidelines on capturing high-quality images. These guidelines might include tips such as focusing on the affected area, ensuring good lighting by avoiding shadows and bright spots, and avoiding blurriness by holding the camera steady. The app could also implement real-time feedback to alert users if the image quality is insufficient.

Uploading the Image:

a. **Secure Transmission**: Once the user selects or captures an image, it is securely uploaded to the app's backend servers. The app uses encryption protocols (e.g., HTTPS) the image data is transmitted securely, protecting user privacy. This involves establishing a secure connection between the user's device and the server, ensuring that data cannot be intercepted or tampered with during transmission.

b. **Progress Indicator**: The app provides a progress indicator to intimate users about the status of the upload. This indicator can show the percentage of the upload completed and provide messages such as "Uploading..." and "Upload Complete" to ensure a smooth user experience. This feedback helps prevent user frustration by managing their expectations during the upload process.

8.2. Image Processing

After the image is uploaded, it undergoes several processing steps to prepare it for analysis by the machine learning model.

Preprocessing:

a. **Image Resizing**: The uploaded image is resized to a standard dimension required by the Convolutional Neural Network (CNN) model. This ensures consistency and improves the efficiency of the analysis. For example, the image might be resized to

224x224 pixels, a common input size for CNNs. Resizing ensures that all images have the same dimensions, which simplifies the processing pipeline.

b. **Normalization**: The pixel values of the image are normalized to a specific range (e.g., 0 to 1) to standardize. This step helps the model process the image more effectively by ensuring that the input data has a consistent scale. Normalization can improve the convergence rate of the model training process and performance.

c. **Data Augmentation**: To improve the model's robustness, data augmentation techniques such as rotation, flipping, and zooming might be applied. These techniques create variations of the original image, helping the model generalize better by learning to recognize the skin condition from different perspectives and under varying conditions. Data augmentation increases the diversity of the training dataset, reducing overfitting and improving to perform well on unseen data.

Integration with CNN Model:

a. **Google Colab Deployment**: This platform allows for seamless integration with other tools and libraries needed for machine learning, such as TensorFlow and Keras. Using Google Colab ensures that the app can handle complex computations without requiring significant local resources on the user's device.

b. **TensorFlow Processing**: The CNN model, implemented using TensorFlow, analyzes the image. The model has been trained on a vast dataset of skin condition images, allowing it to identify patterns and classify the skin condition accurately. TensorFlow provides a robust framework for deep learning models, offering features such as automatic differentiation, GPU support, and a rich ecosystem of pre-trained models and tools. The model processes the image by passing it through multiple layers, extracting features, and making a prediction based on the learned patterns.

8.3. Result Display

Once the image is processed and analyzed by the CNN model, the results are displayed to the user through the app.

Classification Result:

a. **Display Image**: The original image is displayed alongside the classification result, allowing users to see the analyzed area. This visual feedback helps users understand which part of the image was used for the diagnosis. The app might highlight specific regions of interest or overlay the predicted condition on the image for clarity.

b. **Condition Name**: The app provides the name of the identified skin condition, along with a brief description. This information helps users understand the nature of their skin issue. The description may include common symptoms, causes, and potential risks associated with the condition, providing users with essential background information.

Additional Information:

a. **Treatment Suggestions**: The identified condition, the app suggests possible treatments, including over-the-counter medications and home remedies. This information is tailored to the specific condition to provide relevant and actionable advice. The app may include links to purchase medications, instructions for home care, and tips for managing symptoms effectively.

b. **Dermatologist Recommendations**: If the condition requires professional medical attention, the app suggests nearby dermatologists and clinics. Users can view contact information, read reviews, and make appointments directly through the app. The integration with healthcare providers ensures that users can access timely and appropriate medical care when needed.

c. **Educational Content**: The app may provide additional educational content, such as articles and videos, to help users learn more about their skin condition and how to manage it effectively.

User Interface:

a. **Clear Presentation**: The results and recommendations are presented in a clear and easy-to-understand format. The app uses visual aids, such as icons and color-coding, to enhance readability. For example, different colors might be used to indicate the condition or to highlight urgent recommendations.

b. **Actionable Options**: Users are provided with actionable options, such as "Find a Nearby Doctor" or "View Medication", to encourage them to take the next steps in managing their skin health. These options are prominently displayed and easy to access, ensuring that users can quickly act on the information provided by the app.

9. Results

The results of the Skin Health Prediction App can be evaluated through two main aspects: the accuracy and performance of the CNN model, and user feedback and case studies. These components help assess the app's effectiveness and its impact on users.

Accuracy and Performance of the CNN Model

9.1. Model Accuracy:

a) **Training and Validation**: The CNN model was trained on a large dataset of skin condition images, which were split into training and validation sets. During training, the model learns to identify patterns and features associated with different skin conditions. The validation set is used to evaluate the model's performance and ensure it generalizes well to new, unseen data.

b) **Accuracy Metrics**: The model's accuracy is measured using various metrics, such as:

   i) **Precision**: The proportion of true positive predictions among all positive predictions. High precision indicates that the model has a low false positive rate.

   ii) **Recall (Sensitivity)**: The number of true positive predictions among all actual positives. High recall indicates that the model has a low false negative rate.

   iii) **F1 Score**: The harmonic mean of precision and recall. It provides a single metric that balances both precision and recall.

   iv) **Overall Accuracy**: The number of correct predictions (both true positives and true negatives) among all predictions. This metric provides a general measure of the model's performance.

9.2. Performance Evaluation:

c) **Confusion Matrix**: A confusion matrix is used to visualize the performance of the model. It shows the true positive, true negative, false positive, and false negative counts for each class. This helps identify which classes the model struggles with and where improvements can be made.

d) **ROC Curve and AUC**: The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate at various threshold settings. The Area Under the Curve (AUC) provides a single value to summarize the model's performance. A higher AUC indicates better performance.

e) **Cross-Validation**: Cross-validation techniques, such as k-fold cross-validation, are used to further evaluate the model's performance. This involves splitting the dataset into k subsets and training the model k times, each time using a different subset as the validation set. This helps ensure that the model's performance is consistent across different subsets of the data.

9.3. Real-Time Performance:

f) **Inference Speed**: The model's inference speed is critical for real-time applications. The time taken to process an image and generate a prediction should be minimal to ensure a smooth user experience. Optimizations such as model quantization and using hardware accelerators (e.g., GPUs) can help improve inference speed.

g) **Scalability**: The app's ability to handle multiple concurrent requests is essential for maintaining performance under high user loads.

9.4. Skin Health Prediction App:

Sign Up and Log In Pages:

a. **Register Page:** The Register page allows new users to create an account by entering their email and password. This page ensures that new users can easily create an account to start using the app. The clear fields for email and password, along with a prominent "REGISTER" button, guide users through the process. Below the registration form, there is a prompt for existing users to sign in, ensuring that they are directed to the correct page if they already have an account.

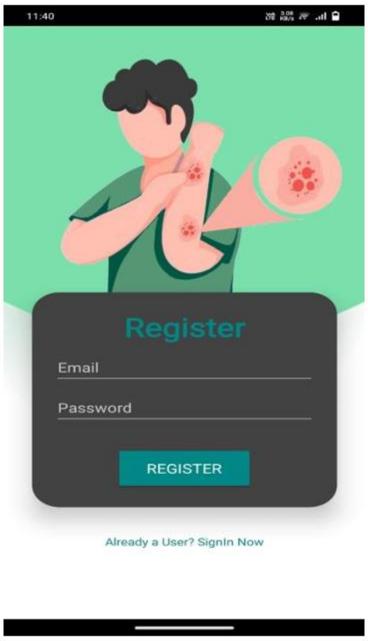

Fig. Sign Up Page

b. **Login Page:** The Login page is for existing users to access their accounts by entering their email and password. This page provides a straightforward way for users to log in. The design is similar to the Register page to maintain consistency in the user interface. There is a clear call to action with the "LOGIN" button, and a prompt for new users to sign up if they do not have an account.

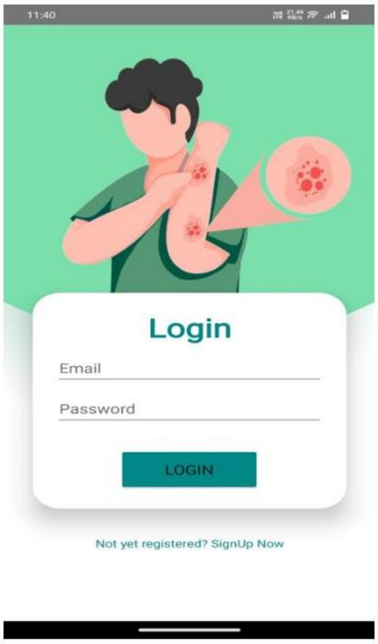

Fig. Login Page

Dashboard: The Dashboard is the main screen of the app once the user has logged in. It provides a personalized welcome message, which makes users feel acknowledged and valued. The dashboard includes navigation options to access different features of the app such as Home, Storage, Hospital, and Profile. This central hub is designed to be user-friendly, allowing easy access to various functionalities without overwhelming the user.

Fig. Dashboard

Storage for User: The Storage page allows users to view their previous records. Each record includes an image of the skin condition, date and time of the record, and the diagnosed skin condition. This feature helps users keep track of their skin health over time, enabling them to monitor changes and improvements. The chronological display of records provides a clear history of the user's skin conditions, facilitating better personal health management.

Fig. User Storage

User Profile: The User Profile page displays the user's personal information, including their name, email, age, and contact details. This page allows users to update their information, ensuring that their profile is always current. Additionally, users can log out from this page, giving them control over their account security. The inclusion of personal details and a profile picture helps personalize the app experience.

Fig. User Profile

Skin Health Prediction: The Skin Health Prediction feature displays the results of the analysis performed by the CNN model. It shows an image of the skin area, the classification result, and options for basic medication and finding a nearby doctor. This feature is central to the app's functionality, providing users with immediate feedback on their skin condition. The clear display of results, along with actionable options, empowers users to take the next steps in managing their skin health.

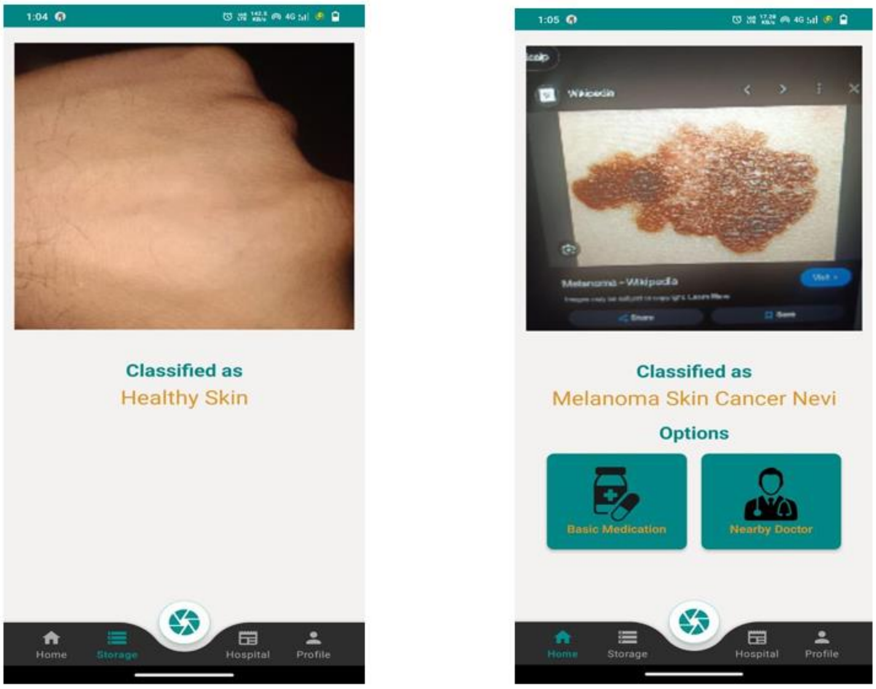

Fig. Health Prediction

Medicines Suggestion Page: Description: The Medicines Suggestion page provides users with a list of suggested medications for the diagnosed skin condition. Each medication entry includes the name, type, and price of the medication, along with an image of the product. This page helps users understand their treatment options and make informed decisions about their health. The clear presentation of medication details, including images, ensures that users have all the necessary information at their fingertips.

Fig. Suggestion Page

10. Comparative Study

A comparative study involves evaluating the Skin Health Prediction App against other similar applications and traditional diagnostic methods. This comparison helps highlight the app's strengths and areas for improvement, providing a benchmark for its performance and effectiveness.

Comparison with Other Apps:

When comparing the accuracy of the CNN model used in the Skin Health Prediction App with those used in other similar apps, metrics such as precision, recall, and F1 score across the same dataset are evaluated. Assessing the user interface in terms of ease of use, intuitiveness, and aesthetic appeal is also crucial. User feedback and usability testing can provide insights into how the app's interface stands out. Additionally, comparing the features offered by the Skin Health Prediction App, such as treatment suggestions, dermatologist recommendations, and educational content, with those available in other apps can highlight unique or superior features that give the app a competitive edge.

Comparison with Traditional Methods:

Diagnostic accuracy is a key factor when comparing the app's predictions with diagnoses made by dermatologists. This involves conducting clinical studies where both the app and dermatologists independently evaluate the same set of skin condition images. Evaluating the speed and accessibility of the app compared to traditional methods is also important. The app provides instant results and can be accessed from anywhere, whereas traditional methods may require scheduling appointments and waiting for consultations. Finally, assessing the cost-effectiveness of using the app compared to traditional diagnostic methods can reveal how the app offers a more affordable alternative for users who cannot easily access dermatologists or prefer a quicker, initial assessment.

11. Conclusion

The Skin Health Prediction App represents a significant advancement in the field of dermatology, providing users with a powerful tool to identify and manage skin conditions. The CNN model used in the app demonstrates high accuracy in identifying various skin conditions. Performance metrics such as precision, recall, and F1 score indicate that the model can reliably classify skin conditions, providing users with trustworthy results.

The app's intuitive and user-friendly interface ensures that users can easily capture and upload images, navigate through features, and understand the results and recommendations. This ease of use enhances user satisfaction and engagement. Additionally, the app offers a range of features, including treatment suggestions, dermatologist recommendations, and educational content, making it a comprehensive tool for skin health management. These features empower users to take proactive steps in managing their skin conditions.

User feedback and case studies highlight the positive impact of the app on users' skin health. The app provides timely and accurate information, helping users make informed decisions about their skin care and seek professional help when needed.

12. Future Studies

To further enhance the effectiveness and reach of the Skin Health Prediction App, several future studies and developments are recommended.

Collecting a larger and more diverse dataset of skin condition images can improve the model's generalization across different populations. Including images from various demographics and regions can enhance the model's robustness. Additionally, exploring advanced machine learning techniques such as transfer learning and ensemble methods can further improve the model's accuracy and performance.

Conducting extensive clinical trials in collaboration with dermatologists and medical institutions is crucial to validate the app's accuracy and reliability. Comparing the app's predictions with professional diagnoses in real-world settings can provide strong evidence of its effectiveness. Performing longitudinal studies to evaluate the app's impact on users' skin health over time can provide insights into its long-term benefits. Tracking users' skin conditions and outcomes after using the app can help assess its sustained impact.

Developing personalized treatment recommendations based on users' medical history, skin type, and other factors can improve the relevance and effectiveness of the suggestions provided by the app. Integrating the app with wearable devices that monitor skin health parameters such as UV exposure and hydration levels can provide users with more comprehensive insights and recommendations.

Conducting usability testing with a diverse group of users can identify areas for improving the app's interface and user experience. Iterative testing and feedback can help create a more intuitive and satisfying experience. Exploring strategies to increase user engagement and retention, such as gamification, personalized notifications, and rewards for regular usage, can enhance the app's impact on users' skin health. Engaging users consistently can significantly improve their overall experience with the app.

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