AI-POWERED SKIN DISEASE DETECTION SYSTEM USING DEEP LEARNING

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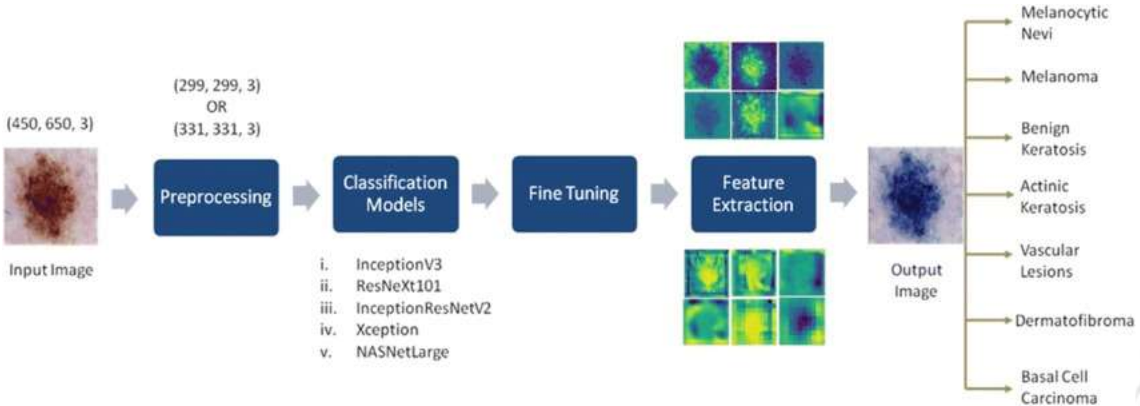
ABSTRACT

Skin diseases are a growing global health concern, with early and accurate diagnosis being crucial for effective treatment. However, limited access to dermatologists and diagnostic tools, especially in remote regions, poses significant challenges. This project proposes an AI-powered web-based skin disease diagnosis system that leverages deep learning and modern web technologies to assist both medical professionals and patients in identifying skin conditions.

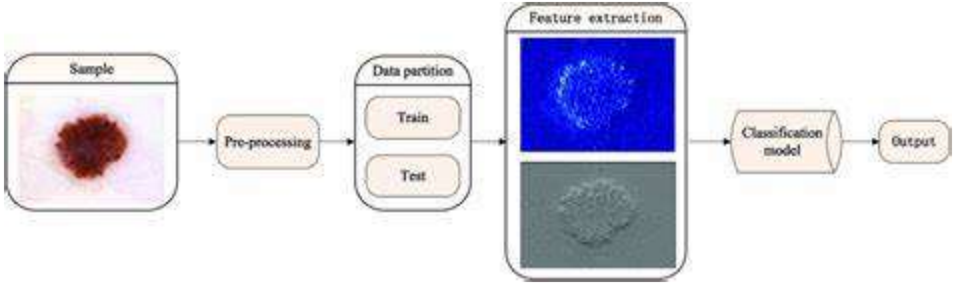
The system utilizes a Convolutional Neural Network (CNN), trained on the HAM10000 dataset, which contains dermoscopic images of various skin diseases. Advanced preprocessing techniques, including image resizing, normalization, and augmentation, enhance model performance and generalization.

Evaluation metrics such as accuracy, precision, recall, and F1-score demonstrate the model's effectiveness in classifying skin diseases with high accuracy. The proposed system is designed as an assistive tool rather than a replacement for medical professionals, bridging gaps in accessibility and efficiency. Future enhancements include expanding the model’s diagnostic coverage, integrating mobile applications, and collaborating with telemedicine platforms. This AI-powered solution has the potential to revolutionize dermatological care by enabling early detection, reducing diagnostic delays, and improving healthcare outcomes worldwide.



AIM

The aim of this project is to develop an AI-powered web-based skin disease diagnosis system that leverages deep learning for accurate and early identification of skin conditions. By integrating a Convolutional Neural Network (CNN) with transfer learning, the system seeks to assist medical professionals and patients in diagnosing common skin diseases efficiently. The project focuses on improving accessibility to dermatological care, particularly in remote and underserved areas. Additionally, it aims to enhance diagnostic accuracy, reduce delays in treatment, and serve as an assistive tool for healthcare providers.



OBJECTIVE

1. Develop an AI-Based Diagnosis System – Implement a deep learning model using a Convolutional Neural Network (CNN) to classify common skin diseases with high accuracy.

2. Enable Image-Based Skin Disease Detection – Allow users to input skin images for real-time diagnosis, providing disease classification and confidence scores.

3. Improve Healthcare Accessibility – Bridge the gap in dermatological care by providing an assistive tool for early detection, especially in remote and underserved areas.

4. Evaluate Model Performance – Assess the model using key performance metrics such as accuracy, precision, recall, F1-score to ensure reliable disease classification.

5. Future Enhancements & Integrations – Explore the potential for expanding the system to detect additional skin conditions, integrating with mobile applications, and collaborating with telemedicine platforms for remote consultations.

Scope of the Work

This project focuses on developing an AI-based skin disease diagnosis system using deep learning techniques. The key aspects include:

Data Collection and Preprocessing – Utilize the HAM10000 dataset, applying preprocessing techniques such as image resizing, normalization, and augmentation to enhance model performance.

Model Development – Implement a ANN Artificial Neural Network Convolutional Neural Network (CNN)

Diagnosis and Classification – The system will analyze input images and provide predictions with confidence scores to assist in skin disease identification.

Performance Evaluation – Assess model accuracy, precision, recall, and F1-score to ensure reliable classification.

Future Enhancements – Expand the dataset, improve model accuracy, and explore integrations with mobile applications and healthcare platforms for broader usability.

This AI-powered system aims to enhance early skin disease detection, improving accessibility to dermatological insights, especially in underserved areas.

Motivation of the Work

Skin diseases are among the most common health concerns globally, yet access to timely and accurate diagnosis remains a challenge, especially in remote and underserved areas. Many individuals lack access to dermatologists, leading to delayed treatments and severe complications. The increasing prevalence of skin conditions and the limitations of traditional diagnostic methods highlight the need for an AI-powered solution.

Deep learning has shown remarkable success in medical image analysis, making it a promising tool for automated skin disease detection. By leveraging AI, this project aims to bridge the gap in dermatological care, providing a cost-effective, scalable, and efficient method for early diagnosis. The motivation behind this work is to improve healthcare accessibility, enhance diagnostic accuracy and reduce the burden on medical professionals, ultimately contributing to better patient outcomes and public health awareness.

Fig. 12. Critical actions for each disease and disease group to reach the 2030 targets

Targeted for eradication

Disease	Critical action 1	Critical action 2	Critical action 3
Dracunculiasis	Develop a scientific and operational protocol for elimination of infections in animals.	Investigate why dracunculiasis infection occurred in Angola to better understand the current challenges and take appropriate measures to stop transmission.	Initiate certification in Democratic Republic of the Congo and Sudan to avoid missing targets.
Yaws	Strengthen active and passive surveillance, including in countries of unknown status.	Ensure effective, efficient integration and/or co-implementation with other programmes and sectors (e.g. integrated management of skin NTDs).	Increase funding and advocacy for yaws eradication, including securing longer-term commitments and increasing the priority of yaws as suitable for preventive chemotherapy and a skin NTD.

Targeted for elimination (interruption of transmission)

Disease	Critical action 1	Critical action 2	Critical action 3
Human African trypanosomiasis (gambiense)	Integrate control and surveillance activities in the peripheral health system; identify and prepare sentinel sites for surveillance post-elimination.	Develop a long-term funding plan, including campaigns for resource mobilization to meet needs.	Reinforce ownership of elimination and targets by endemic countries by advocacy to health authorities and heads of states in the context of decreasing numbers of cases.
Leprosy	Update country guidelines to include use of single-dose rifampicin for post-exposure prophylaxis for contacts; advance research on new preventive approaches.	Continue investment into research for diagnostics for disease and infection; develop surveillance strategies, systems and guidelines for case-finding and treatment; ensure resources for validation.	Ensure medicines supply, including access to multi-drug therapy, prophylactic drugs, second-line treatments and medicines to treat reactions; monitor adverse events (pharmacovigilance) and resistance.
Onchocerciasis	Start MDA in all endemic areas after mapping, improve delivery of current MDA programmes, and implement alternative strategies where appropriate.	Develop improved diagnostics to facilitate mapping and decisions to eliminate transmission; develop improved diagnostic strategy for loiasis; increase programme capacity to perform entomological and laboratory diagnostics.	Develop a macrofilaricide and diagnostic or other elimination strategies to accelerate interruption of transmission; design a case management strategy; develop and implement elimination strategies for areas where loiasis is endemic but onchocerciasis is hypoendemic.

Targeted for elimination as a public health problem

Disease	Critical action 1	Critical action 2	Critical action 3
Chagas disease	Advocate with national or federal health ministries to recognize Chagas disease as a public health problem, and establish effective prevention, control, care and surveillance in all affected territories.	Improve medical care for Chagas disease, from training health care workers in-service to integrating training at all levels of health services.	Ensure that countries in which domiciliary vector transmission is still registered in certain territories comply with prevention, control and surveillance.
Human African trypanosomiasis (rhodesiense)	Develop new field-adapted tools to detect the disease (e.g. rapid diagnostic test) for use in primary health care facilities, and safe and effective treatment.	Integrate control and surveillance into national health systems, and strengthen capabilities through national plans for health care staff for training, awareness and motivation.	Coordinate vector control and animal trypanosomiasis management among countries, stakeholders and other sectors (e.g. tourism and wildlife) through multisectoral national bodies to maximize synergies.
Leishmaniasis (visceral)	Enable early detection to ensure prompt treatment, through, for example, active case detection.	Ensure supply of medicines to ensure prompt access to treatment, especially during outbreaks, and especially for children and young adults, who make up 50–70% of the affected population.	Develop more effective and user-friendly treatment and diagnostics, especially for East Africa.
Lymphatic filariasis	Start MDA in all endemic districts and strengthen it in all settings; implement improved interventions where appropriate (e.g. three-medicine treatment in settings that qualify; strategies for hotspots).	Improve capacity for morbidity management and disability prevention; prioritize in primary health care and as part of universal health coverage.	Improve diagnostics, strengthen criteria for stopping MDA, establish post-MDA and post-validation surveillance standards; update guidelines with new tools and strategies as appropriate.
Rabies	Improve forecasting of demand for rabies vaccine and immunoglobulin to ensure adequate supply in facilities, and develop innovative approaches for delivery to ensure timely access to post-exposure prophylaxis and dog vaccination.	Build national capacity of health workers (e.g. rabies exposure assessment, diagnosis, administration of post-exposure prophylaxis) and for dog management (e.g. mass dog vaccination).	Strengthen and institutionalize surveillance for rabies; improve country compliance with reporting to ensure data availability.
Schistosomiasis	Define indicator for measuring morbidity.	Implement effective interventions, including extending preventive chemotherapy to all populations in need and ensuring access to the necessary medicines; implement targeted snail control with updated guidelines; continue micro-mapping and targeting.	Develop diagnostic tests, including standardized point-of-care diagnostic, and develop new interventions, including alternatives to praziquantel and methods of snail control.
Soil-transmitted helminthiases	Increase political commitment to ensure sustainable domestic financing.	Develop more effective medicines and medicine to improve patient outcomes and in case of drug resistance.	Develop comprehensive surveillance and mapping systems to target treatment and monitor drug resistance.
Trachoma	Improve access to high-quality surgery, tracking of outcomes and management of post-surgery trachomatous trichiasis; initiate management of people with trachomatous trichiasis as soon as possible (about 2.5 million in 2019).	Increase knowledge through research, and extend partnerships to increase work, specifically on facial cleanliness and environmental improvement to reduce transmission.	Develop an efficient, cost-effective way to detect and monitor recrudescence of infection, which could be important for post-validation.

Fig. 12. Critical actions for each disease and disease group to reach the 2030 targets (cont'd)

Targeted for control

Disease	Critical action 1	Critical action 2	Critical action 3
Buruli ulcer	Build capacity of health workers to clinically diagnose and treat the disease and community health workers to detect and refer cases for early treatment, furthering integration among skin NTDs.	Develop rapid diagnostic tools for use in public health and community centres to ensure early diagnosis, reduce morbidity and confirm cases.	Create comprehensive surveillance systems in all endemic countries, including micro-mapping, to improve targeting and integrating interventions with those for other NTDs in co-endemic areas to improve case detection.
Dengue and chikungunya	Continue developing preventive vaccines for all at-risk populations.	Further develop the evidence base on effectiveness of vector control strategies.	Continue collaborating with environmental sector and engineers to reduce mosquito habitats.
Echinococcosis	Map disease prevalence to establish baseline data, and strengthen integrated national surveillance.	Develop guidelines for effective prevention and control strategies, and implement them in the field.	Strengthen implementation of ultrasound diagnosis and effective interventions, and ensure access to albendazole.
Foodborne trematodiases	Develop accurate surveillance and mapping tools and methods, with information on environmental factors involved in infection.	Estimate number of tablets required for control and secure donations of praziquantel.	Promote application and awareness of preventive chemotherapy, WASH and One Health interventions. Evaluate impact, and use the results in training health care staff.
Leishmaniasis (cutaneous)	Develop and scale up easy-to-administer oral or topical treatment that could be used in health centres.	Improve the affordability and sensitivity of rapid diagnostic test for detection of cases, and the availability of treatment.	Estimate the burden of the disease by improving surveillance, and establish a patient database to ensure effective monitoring of the impact of control interventions.
Mycetoma, chromo-blastomycosis and other deep mycoses	Develop differential rapid diagnostic test and effective treatment, and establish surveillance for case detection and reporting.	Develop a standardized field manual for diagnosis and treatment, and ensure proper training of health care workers.	Provide access to affordable diagnosis and treatment.
Scabies and other ectoparasitoses	Develop guidance and tools for mapping in endemic countries to estimate the burden of disease.	Develop guidance for implementation of preventive chemotherapy.	Create an advocacy and funding plan; secure financing for ivermectin and topical treatments; advocate for inclusion in universal health coverage.
Snakebite envenoming	Improve training of physicians in managing snakebite, and build awareness in communities on best practices in prevention and seeking treatment for snakebite envenoming.	Improve the quality of anti-venoms, and invest in research and development of new products.	Enhance overall production capacity for quality-assured products, and ensure their availability and accessibility in rural areas.
Taeniasis and cysticercosis	Develop a high-throughput test for evaluating control programmes in resource-limited settings, and map endemic areas.	Conduct targeted interventions in areas of high endemicity.	Increase advocacy from WHO, FAO and OIE to raise the priority of controlling the diseases.

WHO 2030 GOALS :

Melanocytic nevi
Melanoma
Benign keratosis-like lesions
Basal cell carcinoma
Actinic keratoses
Vascular lesions
Dermatofibroma.

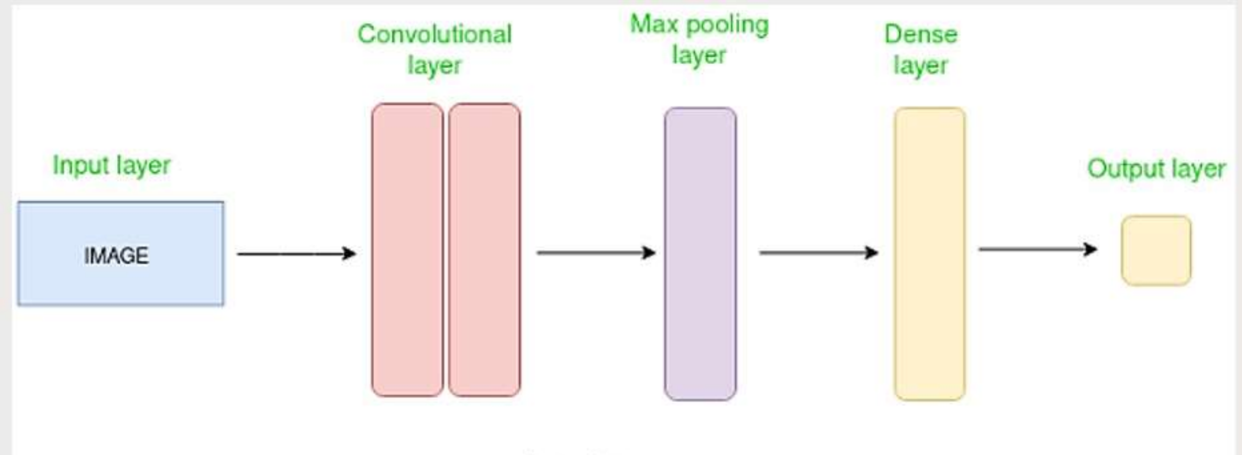
LITERATURE SURVEY

1. Deep Learning and Optimization-Based Methods for Skin Lesions Segmentation (Hosny et al., 2023)【38】

This study provides a comprehensive review of deep learning and optimization techniques for skin lesion segmentation. The research highlights the challenges associated with skin lesion analysis, including unclear boundaries, lighting variations, and class imbalance. The authors compare traditional segmentation approaches with modern deep learning-based methods, emphasizing the advantages of CNNs and optimization algorithms in improving segmentation accuracy. The paper also discusses commonly used datasets such as ISIC, PH2, and Dermofit, which serve as benchmarks for evaluating segmentation techniques.

Deep Learning Models Discussed:

This comprehensive review examines various deep learning architectures utilized for skin lesion segmentation, including Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), U-Net, and Generative Adversarial Networks (GANs).The paper analyzes the strengths and weaknesses of these models in the context of skin lesion analysis.

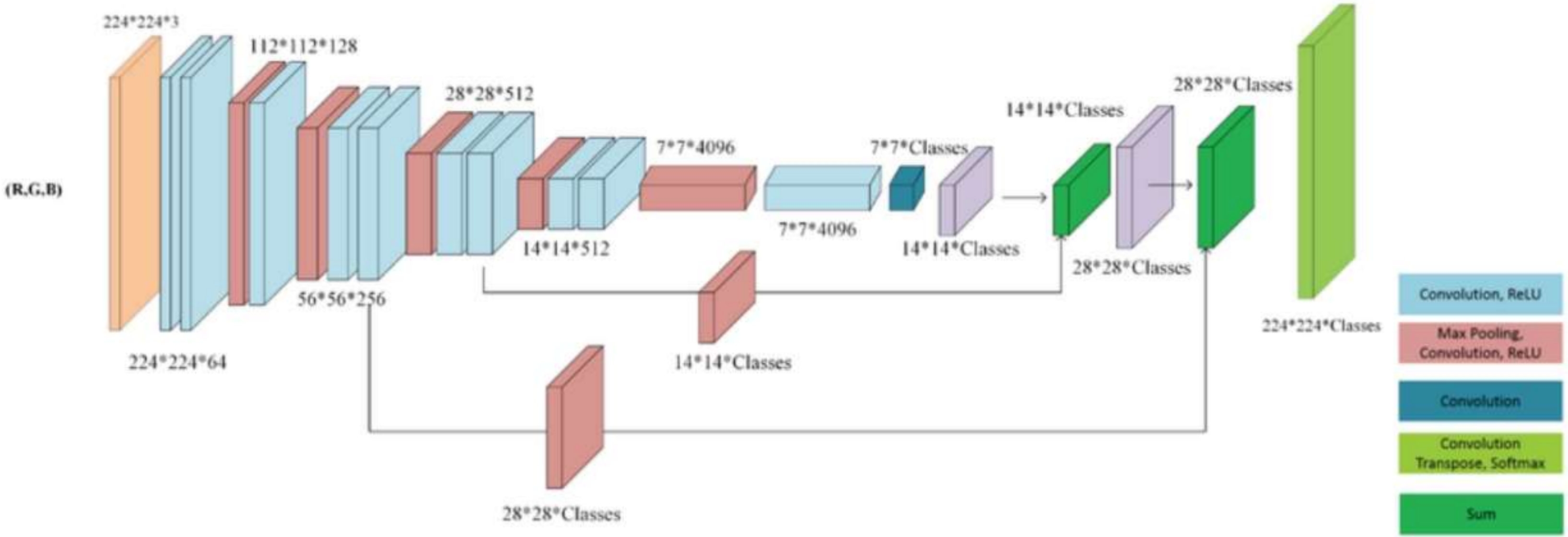


Simple CNN architecture

2. FCN-Based DenseNet Framework for Automated Detection and Classification of Skin Lesions in Dermoscopy Images (Adegun & Viriri, 2020)【52】

This paper proposes an FCN-based ramework for both segmentation and classification of skin lesions. The model incorporates an encoder-decoder architecture with Conditional Random Field (CRF) for contour refinement, improving lesion boundary localization. The classifier enhances feature reuse while optimizing hyperparameters to reduce computational complexity. The model achieved 98% accuracy on the HAM10000 dataset, highlighting the effectiveness of deep learning in skin cancer detection.

Deep Learning Model:
Combines Fully Convolutional Networks (FCNs) to automate the detection and classification of skin lesions in dermoscopy images, benefiting from DenseNet's feature propagation and FCN's pixel-wise prediction capabilities.



Fully convolutional neural network architecture (FCN-8).

3. Pipelined Structure in the Classification of Skin Lesions Based on AlexNet CNN and SVM Model (Sathvika et al., 2024)【55】

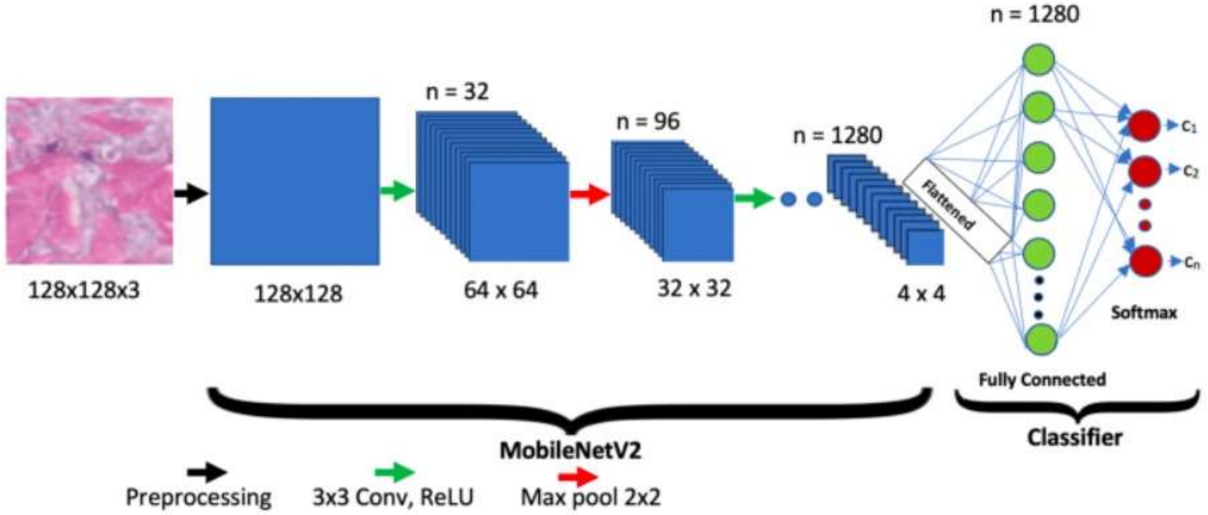
This study explores a two-pipeline approach for skin lesion classification: (1) AlexNet CNN and (2) an SVM model with bi-sectional texture feature extraction. The dataset used includes HAM10000 and PAD-UFES-20. The SVM-based pipeline outperforms AlexNet, achieving 98.66% accuracy, demonstrating the effectiveness of feature extraction techniques in dermatology AI applications. The research emphasizes hybrid models for enhanced classification accuracy.

Deep Learning Model:
Proposes a pipelined structure combining AlexNet Convolutional Neural Network (CNN) for feature extraction with a Support Vector Machine (SVM) for classification, aiming to enhance the accuracy of skin lesion classification.

4. Federated Deep Learning for Monkeypox Disease Detection on GAN-Augmented Dataset (Kundu et al., 2024)【74】

This research integrates federated learning (FL) with generative adversarial networks (GANs) for monkeypox detection, addressing data privacy concerns. The study compares deep learning models such as MobileNetV2, Vision Transformer (ViT), and ResNet50, achieving 97.90% accuracy. The paper highlights the importance of secure AI-driven diagnosis in infectious disease outbreaks.

Deep Learning Model: Implements a federated deep learning approach for Monkeypox detection using MobileNetV2, utilizing a GAN-augmented dataset to improve model generalization while preserving data privacy across multiple institutions.



Source: ResearchGate

DATASET- HAM10000

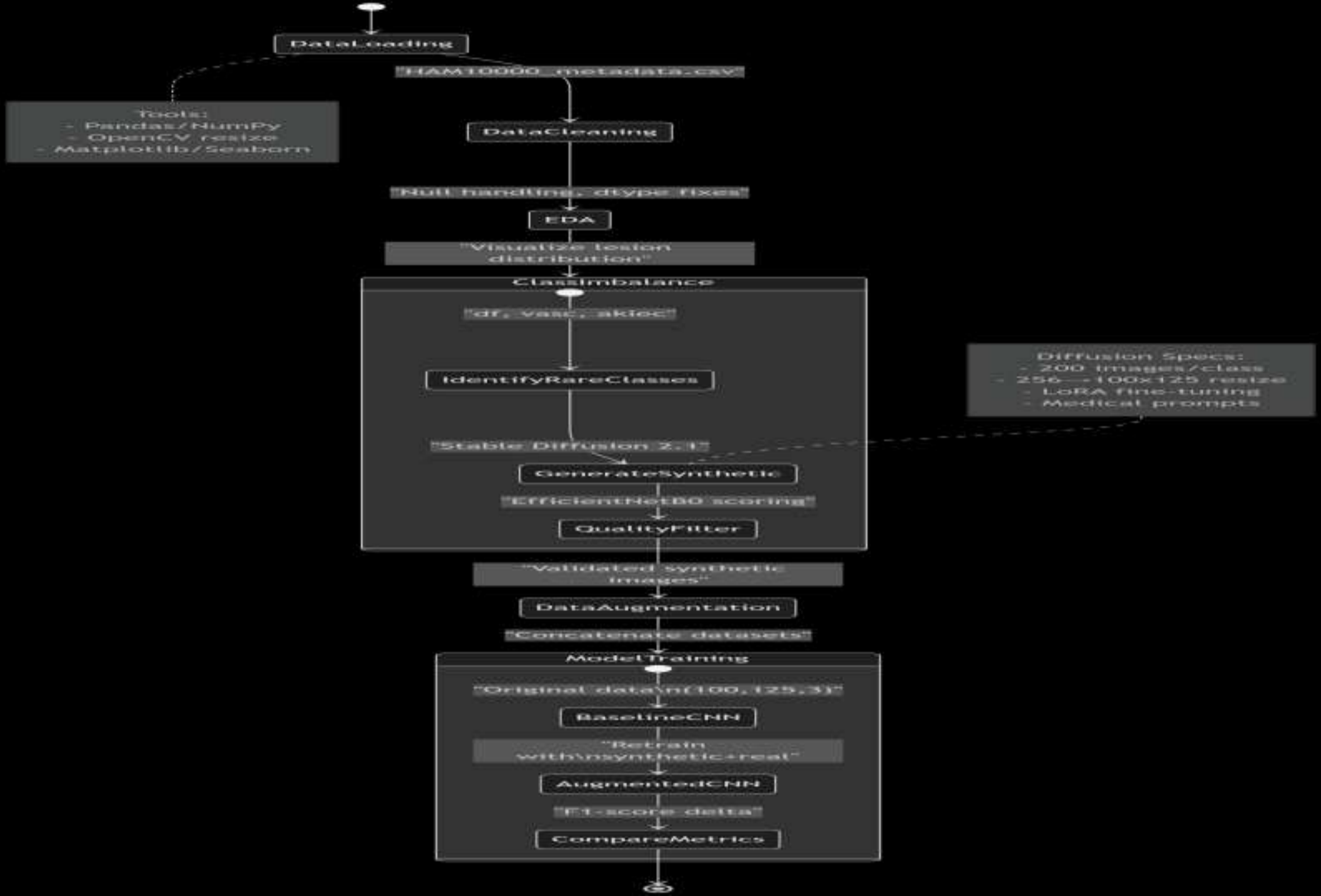
The HAM10000 ("Human Against Machine with 10000 training images") dataset is a large collection of dermatoscopic images used for skin lesion analysis.

It contains 10,015 high-quality images of skin lesions from different patients.

The dataset includes seven types of skin diseases, such as melanoma, nevus, and keratosis.

Each image is labeled and can be used for supervised learning tasks like classification.

It is widely used in medical imaging research for building and evaluating skin disease detection models.



DataLoading
"HAM10000_metadata.csv"
Tools:
- Pandas/NumPy
- OpenCV resize
- Matplotlib/Seaborn
DataCleaning
"Null handling, dtype fixes"
EDA
"Visualize lesion distribution"
ClassImbalance
"df, vasc, akiec"
IdentifyRareClasses
Diffusion Specs:
- 200 images/class
- 256→100x125 resize
- LoRA fine-tuning
- Medical prompts
"Stable Diffusion 2.1"
GenerateSynthetic
"EfficientNetB0 scoring"
QualityFilter
"Validated synthetic images"
DataAugmentation
"Concatenate datasets"
ModelTraining
"Original data\n(100,125,3)"
BaselineCNN
"Retrain with\nsynthetic+real"
AugmentedCNN
"F1-score delta"
CompareMetrics

Methodology & Implementation

- Data Collection & Preprocessing:
  - Source medical images from HAM10000, ISIC Archive, and DermNet.
  - Apply resizing, normalization, augmentation, and noise reduction techniques.
- Model Selection & Training:
  - Use CNN architectures like ResNet50, MobileNetV2, and EfficientNet.
  - Train with 80% data, validate with 10%, and test with 10%.
  - Optimize using Adam optimizer, categorical cross-entropy loss, and early stopping.
- Evaluation Metrics:
  - Accuracy, Precision, F1-Score.

Tentative Proposal Work - MODELS

ANN

An Artificial Neural Network (ANN) is a computational model inspired by the biological neural networks found in the human brain. It consists of three main types of layers:

Input Layer – Receives data in the form of numeric features (e.g., preprocessed image data like color intensity, texture, etc.).

Hidden Layers – Perform complex computations through weighted connections and activation functions (like ReLU or sigmoid) to extract patterns.

Output Layer – Produces final predictions, typically using a softmax or sigmoid activation for classification tasks.

In the skin disease detection project, if we use ANN, we would first need to convert the image into a vector of numeric values (flattening). The ANN can then process this vector to classify it into various categories of skin diseases. However, ANNs do not consider the spatial structure of images, so they often require more preprocessing and may underperform compared to CNNs for image tasks.

Pros in this context:

- Simpler to implement for structured, tabular datasets.
- Can be used if you extract handcrafted features from images (like color histograms or texture metrics).

Limitations:

- Ignores spatial patterns (edges, corners).
- Not ideal for raw image classification.

Accuracy with ANN :

```
670/670 ━━━━━━━━━━━━━━━━━━━━ 22s 32ms/step - accuracy: 0.9387 - loss: 0.1734
Epoch 49/50
670/670 ━━━━━━━━━━━━━━━━━━━━ 20s 30ms/step - accuracy: 0.9455 - loss: 0.1635
Epoch 50/50
670/670 ━━━━━━━━━━━━━━━━━━━━ 23s 34ms/step - accuracy: 0.9329 - loss: 0.1970
78/78 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.6905 - loss: 1.7028
Test: accuracy =  69.08504366874695 %
```

CNN

What is CNN?

A Convolutional Neural Network (CNN) is a type of deep learning model specifically designed for image classification tasks. It automatically extracts features such as edges, textures, and shapes from images using convolutional layers. CNNs are highly effective in identifying patterns and variations in images, which is useful for classifying different types of skin diseases.

Why CNN for Skin Disease Detection?

Skin diseases often show differences in texture, color, and shape. CNNs can:

Automatically learn and extract these features from images

Classify diseases based on learned patterns

Reduce the need for manual feature extraction

Handle image data efficiently through layer-wise processing

CNN Architecture in This Project

1. Input Layer
    - Input images are resized to 100x125 with 3 color channels (RGB).
2. Convolutional Block 1
    - Conv2D: 32 filters
    - Conv2D_1: 32 filters
    - MaxPooling2D: Reduces image size to 50x62
    - Dropout: Prevents overfitting
3. Convolutional Block 2
    - Conv2D_2 and Conv2D_3: 32 filters each
    - MaxPooling2D: Reduces image size to 25x31
    - Dropout: Regularization
4. Convolutional Block 3
    - Conv2D_4 and Conv2D_5: 64 filters each
    - MaxPooling2D: Reduces image size to 12x15
    - Dropout: More regularization
5. Flatten Layer
    - Converts the 3D feature maps into a 1D vector of size 11,520.
6. Fully Connected Layers
    - Dense: 256 units
    - Dense_1: 128 units
    - Dropout: Reduces overfitting
    - Output Dense Layer: 7 units with softmax activation (for 7 disease classes)

How CNN Helps in Skin Disease Detection

- The convolutional layers extract and learn patterns in skin lesion images.
- Pooling layers reduce the image dimensions, making the model faster.
- Dropout layers prevent overfitting during training.
- Fully connected layers combine all extracted features and perform the final classification.
- The model outputs the most likely skin disease class based on the input image.

Accuracy with CNN :

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 22s 698ms/step - accuracy: 0.7124 - loss: 0.8615
28/28 ━━━━━━━━━━━━━━━━━━━━ 13s 460ms/step - accuracy: 0.6916 - loss: 0.8066
Validation: accuracy = 0.699888  ;  loss = 0.767411
Test: accuracy = 0.717019  ;  loss = 0.798288
```

DIFFUSION MODEL:

Diffusion models are generative models that learn to create data by progressively adding noise to real images and then reversing that process to denoise and generate new, realistic samples.

It's like learning how to turn a blurry picture into a clear one, step by step.

Why Diffusion for Skin Disease Detection?

The HAM10000 dataset, while rich, is imbalanced across classes.

Diffusion models help by generating realistic skin lesion images for underrepresented categories.

This balances the dataset and gives the model more variety to learn from.

Applied a diffusion-based image generator to create synthetic skin disease images matching HAM10000 patterns.

These synthetic images were added to the training set as data augmentation.

Helped our model focus on fine-grained features like mole borders, texture, and discoloration.

Future Prospects & Challenges

•Addressing Dataset & Bias Issues: Expanding and diversifying datasets will enhance model accuracy and reduce biases in AI-driven diagnostics.
•Explainability & Ethical AI: Implementing explainable AI models ensures transparency and trust, allowing healthcare professionals to interpret AI-driven decisions effectively.
•Regulatory & Privacy Concerns: Addressing data privacy and ensuring seamless integration with existing healthcare systems are crucial for widespread adoption.
•Shaping the Future of AI in Healthcare: With ongoing research and multidisciplinary collaboration, AI-powered diagnostics have the potential to transform global healthcare, making early disease detection a universal reality.

Conclusion – AI-Powered Skin Disease Detection System

•Revolutionizing Medical Diagnosis: This system showcases the potential of deep learning, particularly CNNs, in accurately detecting and classifying skin diseases from medical images.
•Enhanced Clinical Decision-Making: AI-powered diagnostics assist dermatologists by providing quick and accurate preliminary assessments, improving early disease detection and reducing diagnostic errors.
•Improved Accessibility: The system can be especially impactful in under-resourced areas, where limited access to dermatologists makes AI-driven tools invaluable for early intervention.
•Encouraging Results: Extensive model training and validation on diverse datasets have demonstrated high accuracy in differentiating between various skin conditions.

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