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# Leprosy Identification with AI analysis by Integrating Skin Lesion Images and Clinical Data

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**ABSTRACT:** The convergence of artificial intelligence (AI) within healthcare has ushered in a groundbreaking approach to leprosy identification, fusing image analysis of skin lesions with clinical data analysis. Through the adept utilization of Convolutional Neural Networks and deep learning, AI algorithms scrutinize lesion images, detecting nuanced patterns indicative of leprosy. Simultaneously, these algorithms delve into patient history and symptoms, amalgamating visual and clinical data to furnish a holistic diagnostic tool. This symbiotic relationship between AI and medical professionals augments early detection, precise classification, and more effective patient care. It's crucial to recognize AI as a complement to the expertise of healthcare practitioners, synergistically bolstering efforts to combat leprosy and elevate healthcare outcomes.

**KEYWORDS:** leprosy Identification, VGG16, ResNet50V2, Baseline, Machine learning, Deep learning, Automated detection, Skin disease detection

## I. INTRODUCTION

Leprosy, also known as Hansen's disease, has been a persistent challenge in the realm of infectious diseases, particularly in regions with limited resources and access to healthcare. The identification and management of leprosy cases have often relied on traditional diagnostic methods, but the integration of artificial intelligence (AI) introduces a transformative approach. This essay explores the significance of AI analysis, focusing on the amalgamation of skin lesion images and clinical data for a more comprehensive understanding of leprosy.

Leprosy is a chronic infectious disease caused by *Mycobacterium leprae*, affecting the skin, peripheral nerves, and, in severe cases, other organs. The characteristic skin lesions associated with leprosy have been a central element in its diagnosis. However, the variability in clinical manifestations and the gradual onset of symptoms make accurate and timely identification challenging. The introduction of AI into leprosy identification brings forth a promising solution, leveraging advanced technologies to analyze both visual and clinical data. The integration of artificial intelligence (AI) in leprosy diagnosis signifies a pivotal advancement in addressing the persistent challenges linked with this chronic infectious disease. By merging skin lesion images with clinical data, AI algorithms offer a comprehensive analysis, enhancing the precision and efficiency of diagnosis. This innovative approach transcends traditional diagnostic limitations, such as subjective assessments, by providing objective insights and enabling early detection essential for timely interventions.

Machine learning (ML) and deep learning (DL) techniques have emerged as valuable tools in the detection and diagnosis of diseases such as leprosy. By leveraging advanced algorithms, ML and DL facilitate the analysis of medical images depicting characteristic skin lesions associated with leprosy. Through image recognition and feature extraction,

these algorithms can identify subtle patterns and features indicative of the disease, enabling early and accurate diagnosis. Supervised learning methods, including support vector machines and deep neural networks, play a crucial role in classifying skin lesions as indicative of leprosy or not.

## II. LITERATURE SURVEY

In order to get required knowledge about various concepts related to the present application, existing literature was studied. Some of the important conclusions were made through those are listed below.

**Cooreman E, Gillin L, Pemmaraju V, et al[1]:** Addressing legislators, medical professionals, and others impacted by the disease, the publication "Guidelines for the Diagnosis, Treatment, and Prevention of Leprosy" provides a thorough framework for addressing the disease's intricacies. It emphasizes the need of using evidence-based strategies to deal with issues like drug-resistant strains, clinical ambiguity, and difficulties with early detection and prevention. Notably, it stresses surveillance for tracking medication resistance and addresses the effectiveness of shorter treatment cycles. For those involved in the control of leprosy, this resource is essential since it offers insights into diagnosis, treatment, and prevention techniques based on available data and highlights areas that require more study and intervention.

**Barbieri RR, Manta FSN, Moreira SJM, et al[2]:** According to the study, qPCR has a better sensitivity (57% vs. 35%) than histology when it comes to identifying PB leprosy. It implies that qPCR can be useful in detecting instances with nonspecific histology characteristics, particularly when histopathological changes are not sufficient. The usefulness of qPCR in improving leprosy diagnosis precision and clinical management is highlighted by the fact that simultaneous qPCR and histology boost PB diagnosis sensitivity without losing specificity.

**Richardus JH, Tiwari A, Barth-Jaeggi T, et al[3]:** This research addresses the Leprosy Post-Exposure Prophylaxis (LPEP) initiative, which integrates the administration of single-dose rifampicin (SDR) in six countries with contact tracing. Using the GRADE method, evidence-based SDR recommendations were created, with academic partners guaranteeing quality and index patient and contact-focused data collecting. The study was planned, carried out, and reported by authors and contributors who also provided technical solutions and modified techniques to overcome obstacles. While some authors worked as advisors or on the steering committee, coordination was handled by the Novartis Foundation and partners of the International Federation of Anti-Leprosy Association. Decisions about publication and data interpretation were made independently of the funding source.

**Ridley DS, Jopling WH [4]:** The article describes how leprosy is currently classified according to immunological response and bacterial burden into three groups: tuberculoid, borderline, and lepromatous. Some argue for improved disease reflection by proposing a change to a two-group system, paucibacillary and multibacillary. A more precise classification might improve studies on risk variables, the course of diseases, and the creation of treatments. Any modifications must, however, be thoroughly validated by study.

**Brinker TJ, Hekler A, Enk AH, et al[5]:** Deep convolutional neural networks (CNNs) have been significant in the diagnosis of skin cancer, offering automatic categorization in spite of the intricate heterogeneity in lesion appearances. Dermatologists were surpassed by a CNN trained on an extensive dataset in differentiating between benign seborrheic keratoses and keratinocyte carcinomas, as well as between malignant melanomas and benign nevi. This shows that AI has the ability to accurately categorize skin cancer and, by integrating mobile devices, expand diagnostic knowledge outside of clinical settings.

**Marchetti MA, Liopyris K, Dusza SW, et al[6]:** In order to improve dermatologists' accuracy in identifying melanoma using dermoscopy images, the study evaluated computer algorithms from a melanoma detection challenge. With an AUC of 0.87, the most effective algorithm greatly beat doctors and dermatology residents. Enhancing dermatologists' sensitivity and specificity was achieved by incorporating algorithm classifications with low confidence ratings. Notwithstanding these drawbacks, the study underscores the potential of deep neural networks to improve human performance in the diagnosis of skin cancer, underscoring the significance of utilizing machine learning in dermatology.

### 2.1 Literature review summary

The revolutionary potential of combining AI analysis with clinical data and skin lesion photos for leprosy identification has been highlighted in recent work. This method, which makes use of cutting-edge machine learning algorithms, improves diagnostic efficiency and accuracy while promoting early intervention and treatment. Combining clinical

knowledge with image analysis allows for a more thorough evaluation that is faster and more accurate than with conventional techniques. The challenges encompass verifying dependability in various demographics and environments, managing data privacy issues, and guaranteeing accessibility in areas with restricted resources. All things considered, the application of AI has great potential to transform leprosy management, diagnosis, and eradication efforts across the globe.

### III. PROPOSED SYSTEM

Increasing evidence around machine learning enabling faster and more accurate image-based diagnosis in disciplines such as radiology, pathology, and dermatology, motivated us to develop an Artificial Intelligence (AI) driven “diagnosis accelerator” for leprosy, AI4Leprosy, using a combination of skin images, clinical and reported symptoms. Most of the AI-driven diagnosis evidence in dermatology comes from melanoma, and algorithms such as deep convolutional neural networks (CNN) have delivered comparable accuracy to dermatologists, in differentiating malignant from benign lesions. Deep neural networks have shown to exceed specialists in differentiating melanoma from benign mimickers such as nevi and seborrheic keratoses on dermo scopy images.

Larger training datasets and advances in algorithm development further increased its performance, while augmenting human performance for lesions where physicians reported low diagnostic confidence.

### IV. METHODOLOGY

As the predictive models we used require equal input dimensions, we developed a two-step patient-level model, first predicting the probability of leprosy based on the skin lesion image (Model 1) or the metadata (Model 2). Each model produced a probability of leprosy for each image or set of metadata, as shown in Figure 1. Given that patients could have multiple lesions or metadata records, we combined outputs from both models per patient in a histogram, to represent the predicted probabilities. Lastly, Model 3 was trained to combine analysis made in the first step, with the patient information. This last step established the overall probability by combining the histograms from Model 1 and 2, with patient information.

#### Data modelling overview.

Of the 228 recruited patients, 222 patients were finally included in the data analysis. Images (model 1) or metadata (model 2) from 182 patients were used to train the algorithms in a training dataset, while 40 patients were separated as an independent testing group only used for validation in model 3. The outputs of models 1 and 2 were histograms that fed the accuracy and area under curve (AUC) calculations

#### Training Stage

In the training stage, the system is given a collection of patient Leprosy data. This data includes patient information, metadata (data about data), and a binary label indicating the presence or absence of leprosy. There are 294 skin disease images from web out of which we consider Acne, Psoriasis, Leprosy. This data is fed into a machine learning model, which is a computer program that learns to identify patterns in data. The model goes through an iterative process of being presented with the training data, making predictions about the presence of leprosy, and then being corrected based on the known binary labels for each patient. This process continues until the model reaches a satisfactory level of accuracy.

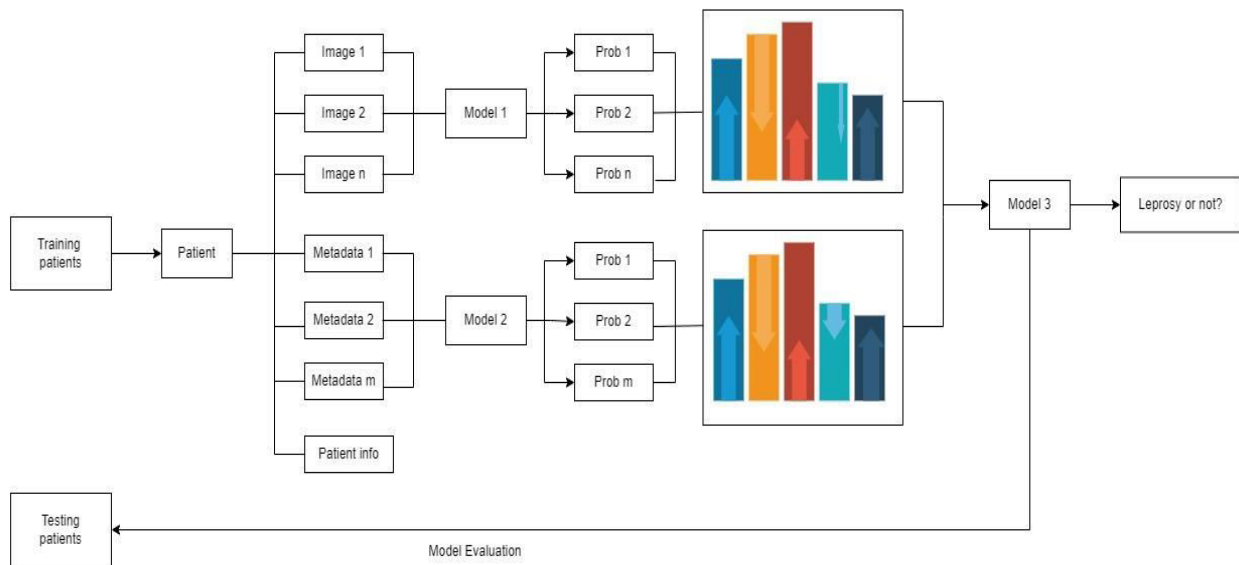


Fig 5.1: Methodology diagram

### Testing Stage

In the testing stage of the leprosy diagnosis model, the process involves inputting the metadata of new patients into the trained model. This metadata typically includes various clinical data such as patient history, demographic information, and possibly laboratory results. The model considers 10% of data for testing. The model then utilizes its learned patterns and algorithms to analyze this data and generate a probability score indicating the likelihood that the new patient has leprosy. This probability score serves as the output of the model, providing healthcare professionals with valuable results of positive or negative.

The output probability generated by the model serves as a quantitative assessment of the likelihood of leprosy, assisting healthcare professionals in making informed decisions regarding further diagnostic testing or interventions.

As with any diagnostic tool, ongoing validation and refinement are essential to ensure the model's accuracy and effectiveness in real-world clinical settings.

### Evaluation

Evaluation of the leprosy skin disease classifier model was based on its accuracy in predicting leprosy disease from images. The model achieved an accuracy of 88% on the test set, indicating its potential for accurate diagnosis of leprosy disease. However, the evaluation also revealed some limitations of the model, including its sensitivity to image quality and potential biases in the training dataset. These limitations suggest the need for further improvement and validation of the model before it can be applied in clinical settings. Overall, the evaluation highlights both the strengths and weaknesses of the model and provides insights for future development and refinement.

V. RESULTS

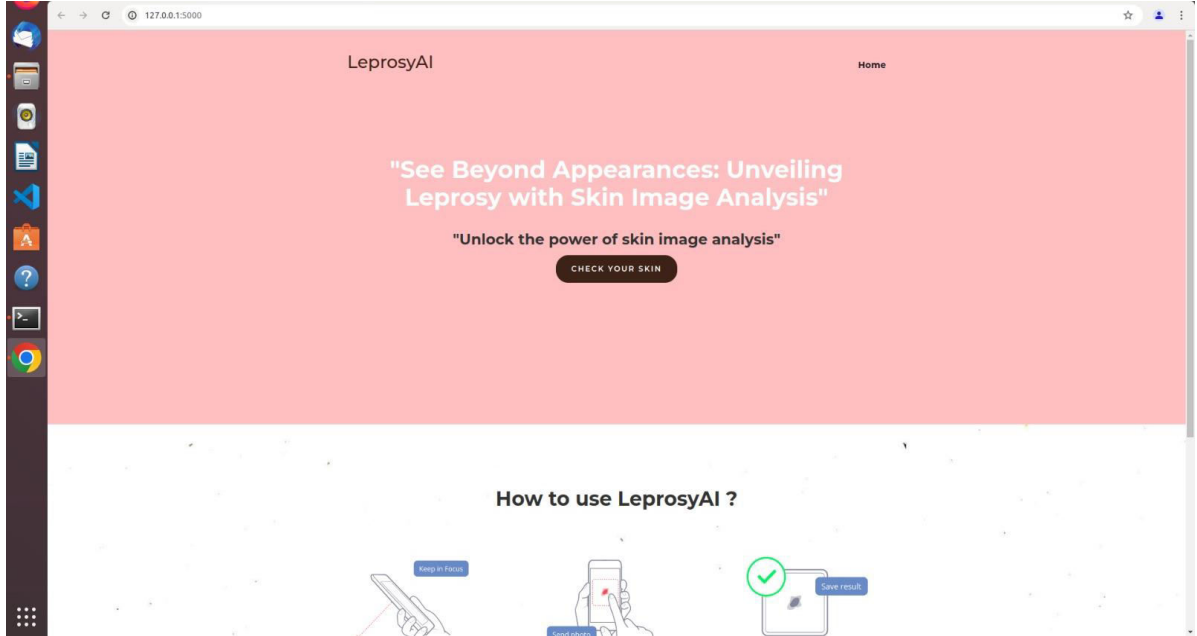


FIG 5.1: FRONT PAGE OF WEBSITE

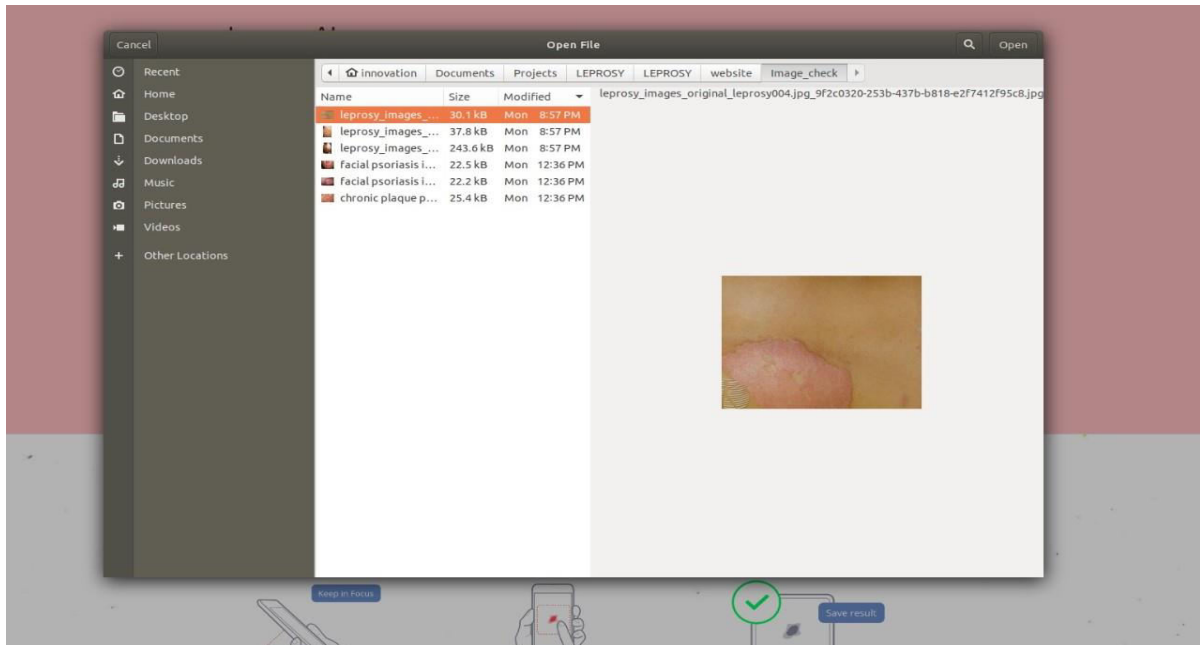


FIG 5.2: SELECTING AN IMAGE OF PATIENT

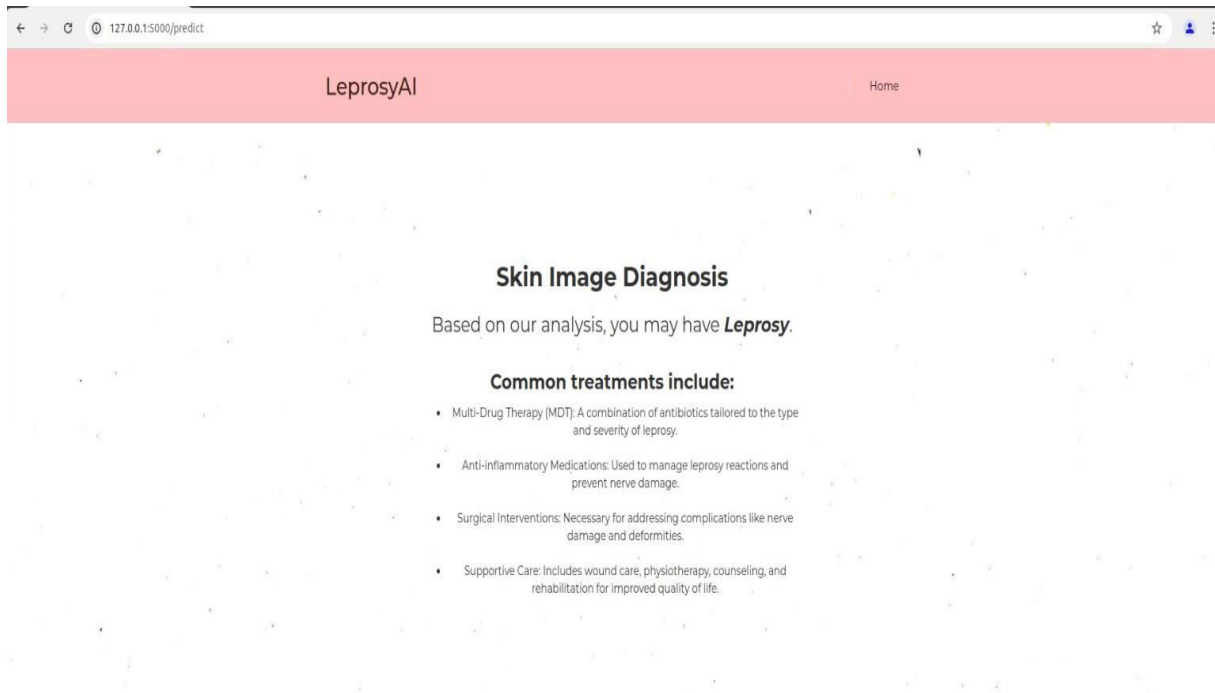


FIG 5.3: PATIENT DIAGONISED WITH LEPROSY

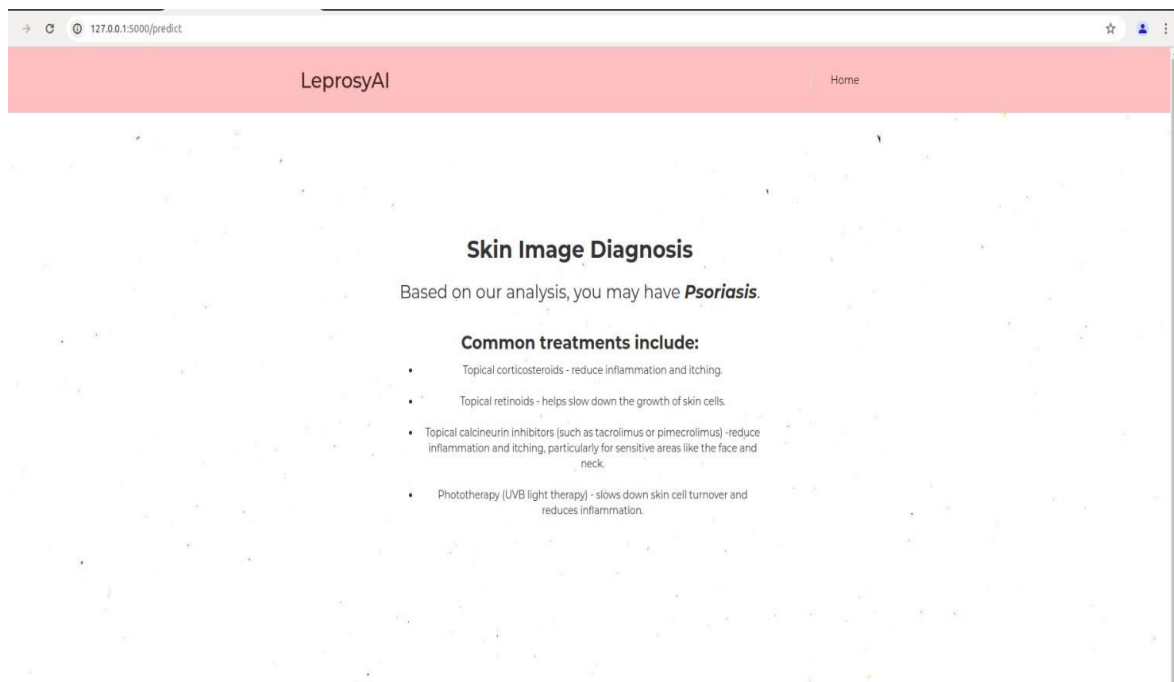


FIG 5.4: PATIENT DIAGONISED WITH NON-LEPROSY

## VI. CONCLUSION

A novel strategy to leprosy identification and management is presented via the integration of AI analysis with skin lesion photos and clinical data. This approach improves diagnostic efficiency and accuracy through the use of cutting-edge machine learning algorithms. It provides a thorough evaluation, outperforming conventional techniques in accuracy and promptness, allowing for early intervention and treatment. Image analysis and clinical insights work

together to achieve this. Despite its potential, more study is required to confirm its dependability across a range of demographics and environments, tackling issues like data privacy and accessibility in areas with low resources. Furthermore, beyond diagnosis, AI-driven analysis has the potential to completely transform leprosy monitoring and management by enabling dynamic skin lesion assessment over time, following the progression of the illness, assessing the effectiveness of treatment, and customizing patient care. To fully realize AI's transformational potential, interdisciplinary collaboration and responsible use are essential.

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