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Computer Assisted Model for Auto Immune Skin Disease

Pranjal Raj[1], Pratyush Arora[2], Sini Anna Alex[3], Sagar Nainwani[4] and Shriya R Onkar[5]
[1-2,4-5]Department of CSE(AI&ML), Ramaiah Institute of Technology, Bangalore, Karnataka
Email: 1ms21ci039@msrit.edu, 1ms21ci040@msrit.edu, 1ms21ci048@msrit.edu,
[3]Senior Member, IEEE
Email: sinialex@msrit.edu

***Abstract*— A timely and accurate diagnosis of auto-immune skin diseases is essential for treatment. This project describes a new system involving deep learning techniques that detect auto-immune skin diseases. This is achieved via Convolutional Neural Networks (CNNs) that can categorize and identify skin diseases in real-time, assisting both patients and healthcare professionals. The project has data collection, preprocessing, model training and evaluation. The system is trained with quality medical datasets, including patient demographic data and skin image data, to ensure the system is robust and generalizable. This includes a trained model achieving an overall accuracy of 84% on a test dataset of 21,000 images. The development of a simple-to-use web interface with Flack that will allow for the reporting of the potential skin disease(s) in real-time to both you and the trained model. The user can upload images and receive diagnostic results that will empower them in their skin health decision making, including whether they need medical guidance in a timely manner. The system provides: Improved Diagnostic Accuracy: Reduces the chance for misdiagnosis, where the need for speedy and accurate treatment is crucial; Improved Access to Healthcare: The system provides diagnostic services to regions underserved by dermatologists; Improvement to Dermatologists: Provides accurate diagnostics used during consultations in developing personalized treatment pathways. Through an early detection and accurate diagnosis based on deep learning procedures, the project will help to improve the management of auto-immune skin diseases, which ultimately has an effect on improved treatment pathways and quality of life for patients. The principles of combining care with technology, one chip at a time.**

***Keywords*— Auto-immune skin diseases, deep learning, Convolutional Neural Network, real-time diagnosis, healthcare, dermatology, diagnostic accuracy, personalized treatment.**

I. INTRODUCTION

Autoimmune skin diseases, including psoriasis, lupus, and vitiligo, arise when the immune system incorrectly attacks healthy skin cells, impacting the psychosocial well-being of patients. Autoimmune skin diseases must be managed by identification; therefore, an accurate and prompt diagnosis must be made. Diagnosing disease has typically involved use of multiple approaches for a diagnosis, such as visual evaluation as performed by the dermatologists, skin biopsy and laboratory statistics, all of which can be lengthy and have a margin of human error.

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Machine learning (ML) and deep learning (DL) can revolutionize diagnosis, thus increasing accuracy and time of diagnosis of autoimmune skin diseases. These technologies can analyze large datasets, detect subtle patterns, and provide consistent results, making them highly suitable for medical applications(Liu S, Liu Y, 2025). This research aims to develop a computer-assisted model for diagnosing autoimmune skin diseases using advanced ML techniques, supporting healthcare providers and improving patient outcomes.
Early detection and diagnosis are critical in managing health and diseases. The challenge lies in developing a reliable system that can classify and detect various autoimmune skin diseases using ML algorithms, addressing the limitations of traditional methods (Vasuja Devi Midasala , 2024).

A. Objectives

- Design and develop a deep learning model capable of accurately diagnosing various autoimmune skin diseases.
- Create a user-friendly web application for easy access to diagnostic tools.
- Provide personalized treatment recommendations based on the diagnosis.
- Implement real-time monitoring and diagnostic capabilities.

B. Organization of the Paper

The paper is structured as follows: Section I Introduction Section II reviews related work in autoimmune disease detection using ML. Section III presents the proposed architecture for the diagnostic system. Section IV details the implementation and configuration of the system and evaluates the model's performance using real-world datasets, discusses the results, advantages, and limitations. Finally, Section V concludes the paper and suggests future research directions.

II. Related Work

A. Overview of Existing Approaches

Traditional diagnostic methods for autoimmune skin diseases often fail to capture the complexities of these conditions, leading to diagnostic delays and suboptimal treatment. Advances in artificial intelligence (AI) and ML offer promising solutions to these challenges (Niccolò Capurro, 2024).

B. Hardware-Based Redundancy

Hardware redundancy employs multiple sensors and systems to ensure reliability, commonly used in critical applications. In autoimmune skin disease detection, this could involve multiple imaging devices and diagnostic tools to cross-verify results and enhance accuracy (Falaschetti, Laura , 2024).

C. Analytical Redundancy

Analytical redundancy uses models to predict sensor readings and identify discrepancies. This method can simulate the progression of autoimmune skin diseases and compare actual patient data to detect anomalies (Xiangwen Shi , 2024).

D. Model-Based Approaches

Model-based approaches use mathematical models to represent systems and diagnose faults. In dermatology, detailed models of skin anatomy and pathology can aid in the detection and classification of skin diseases (Federica Li Pomi, 2024).

E. Data-Driven Techniques

Data-driven techniques leverage data mining and ML to identify patterns and anomalies in large datasets. (Fuyu An, Kai Wang, 2024). For autoimmune skin disease detection, these methods can analyze patient histories, genetic data, and skin images to provide accurate diagnoses Xian Chen, Zhe Yan, 2024) State-of-the-Art Architectures. Frameworks like MoSIoT and applications such as the iShU app integrate ML and IoT for personalized healthcare (Rifat Sadik, 2023). These systems use cloud computing and mobile applications to provide real-time diagnostic and monitoring capabilities, enhancing patient care (David S. Pisetsky, 2023).

F. Gaps in Existing Literature

- Despite advancements, challenges remain in AI-based healthcare diagnostics:
- Integrating advanced AI with existing healthcare systems.
- Standardizing data formats for interoperability across different platforms.

- Conducting extensive clinical trials to validate AI models.
- Ensuring AI models generalize well across diverse patient populations.
- Addressing ethical and regulatory issues to protect patient privacy and ensure responsible AI use in healthcare.

III. Architectural Overview and Implementation

A. Architectural Overview

The proposed Computer-Assisted Diagnostic for Autoimmune (CADIA) architecture aims to leverage spatial and temporal dependencies in sensory data to deliver accurate, real-time diagnostics for autoimmune skin diseases. This modular architecture comprises several essential components: Data Collection Module, Preprocessing Module, Model Development Module, and User Interface Module (Fuyu An, 2023).

B. Data Collection Module

This module focuses on gathering diverse medical datasets crucial for training and validating the machine learning models.

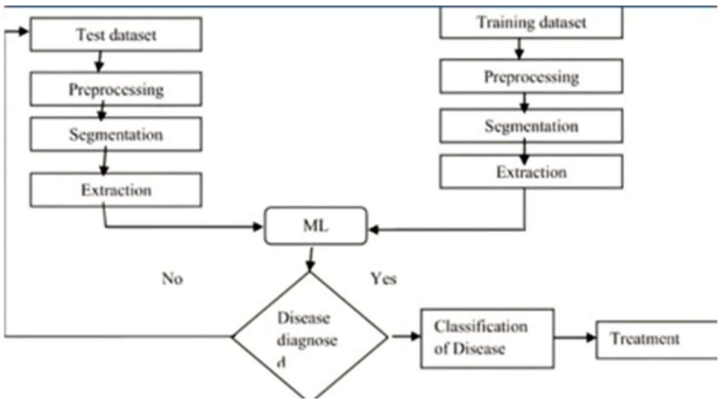

Fig 1: Low level design for diagnosing Autoimmune skin disease

Public Dermatology Datasets: Utilize publicly available datasets with high-resolution images of various skin conditions.

- Clinical Data: Collaborate with hospitals and clinics to obtain clinical data, including patient histories, lab results, and images(Olivia Casey, 2023).
- Patient-Contributed Data: Collect data directly from patients through online platforms and providing a diverse and real-world data sample.

C. Preprocessing Module

The Preprocessing Module ensures the quality and consistency of the collected data, preparing it for model training and evaluation.

Data Cleaning

- Removal of Incomplete Records: Identify and remove records with missing or incomplete information.
- Handling Missing Values: Use imputation techniques to fill in missing values, ensuring a complete dataset.

Data Normalization

- Standardizing Image Sizes: Resize all images to a consistent size and resolution for uniform input to the neural network.
- Pixel Value Normalization: Normalize pixel values to a standard range (e.g., 0 to 1) to ensure consistent model input.

Data Augmentation

- Rotation: Randomly rotate images to simulate different viewing angles.
- Flipping: Apply horizontal and vertical flipping to increase data diversity.
- Scaling: Randomly scale images to simulate different distances and sizes.
- Color Jittering: Adjust brightness, contrast, and saturation to account for varying lighting conditions.

D. Model Development Module

The module focuses on developing, training and fine-tuning a Convolutional Neural Network (CNN) model, specifically a modified ResNet-34 model, for accuracy and robustness. The ResNet-34 model architecture will capture, refine, and classify features obtained from input images. The ResNet-34 model architecture is well suited to identify autoimmune skin diseases.

Initial Convolutional Layer

The model begins with the first convolutional layer which has a 64 filter, 7x7 convolution and a stride of 2. This layer is important for initial feature extraction as it has a larger receptive field to first extract broad and necessary features from the input image. This is a pivotal foundation for extracting more details of features in the subsequent layers (Hammad, M., Pławiak, P, 2023).

Max Pooling Layer

After the first convolutional layer, the architecture has a 3x3 max pooling layer with a stride of 2 to reduce the spatial dimensions of the feature maps, and eliminate redundancy as much as possible to reduce computational complexity and still keep desired features. This operation is also very important in controlling overfitting and ensure that the network learns the most relevant, salient features of the input images (Zhang J, Zhong, 2023).

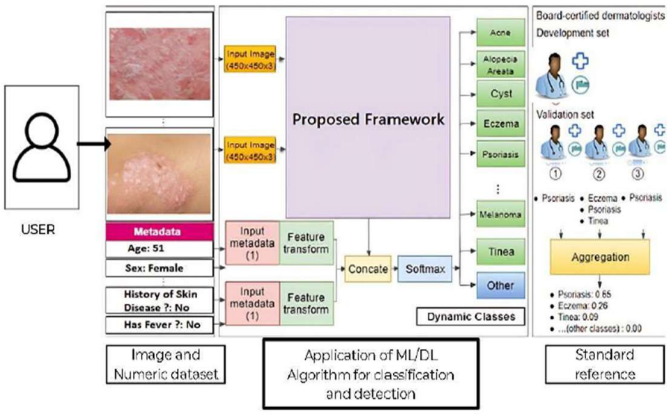

Fig 2: Proposed Framework of Computer Model for Autoimmune skin disease

Residual Blocks

The core of the ResNet-34 architecture is made up of a series of groups of residual blocks that progressively extract and refine features through a number of convolutional layers:

- Layer group 1: This layer group contains three residual blocks, each of which contains two 3x3 convolutional layers using 64 filters. These blocks have a identity shortcut included, which can reduce the effects of the vanishing gradient issue, by allowing a pathway for the gradients during back propagation, to flow through the network much easier. Layer group 1 is focused on taking embryonic features and refining them.
- Layer group 2: Here the network is tasked with processing progressively more complex features and containing the residual blocks with two 3x3 convolutional layers with 128 filters. the first block in layer group 2 uses a stride of 2 to down sample the image so that the input width and height are halved, this means that the feature map (output of layer 1) is down sampled to allow the network to deal with progressively larger more abstract features. The down sampling here takes place by adding an element of extra reduction in the width and height input size which assists in helping manage the models capacity and utilization (Ennio Giulio Favallia, 2022).
- Layer group 3: This group includes six residual blocks, each of which contains two 3x3 convolutional layers with 256 filters. Taking the network deeper enables the extraction of higher level features and representations from the input data. Approximately on the similar wavelength to layer groups (1 & 2), layer group 3 allows the network to learn more exotic patterns and useful detail of the sthece image.Layer Group 4: The final group consists of three residual blocks with two 3x3 convolutional layers having 512 filters each. This group captures the most abstract and complex features, ensuring the model can learn and recognize intricate patterns and details necessary for accurate classification.

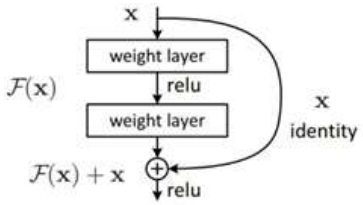

Fig 3: Global Average Pooling Layer

To minimize overfitting and ensure a more generalized model, the architecture includes a global average pooling layer. This layer reduces each feature map to a single value by averaging all the values in each feature map. This step not only reduces the dimensionality of the data but also helps the model generalize better by focusing on the most important features (Shuchi Juyal, Sachin Sharma, 2021).

E. Training Process

- Loss Function: Cross-entropy loss is used to optimize classification performance by measuring the difference between predicted and actual labels.
- Optimizer: Adaptive Moment Estimation (Adam) is employed for efficient and effective convergence during training, adjusting learning rates based on gradient estimates.
- Evaluation Metrics: Accuracy, precision, recall, and F1-score are used to evaluate the model's performance, ensuring a comprehensive assessment of its diagnostic capabilities.

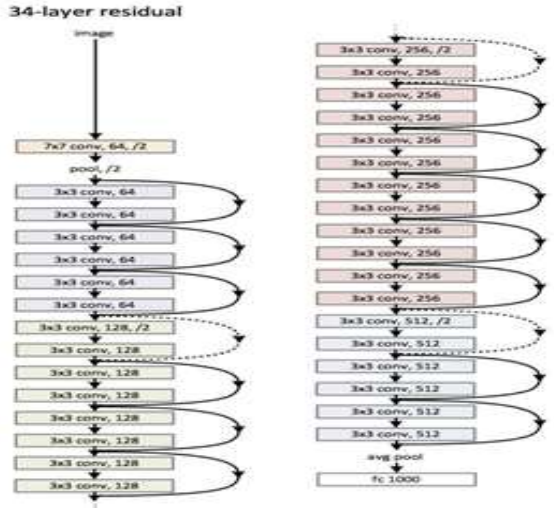

Fig 4: Residual Layer

F. Tools Introduction

The implementation phase involves the execution of various tools and technologies for building the system to diagnose autoimmune skin diseases. The tools utilized in this project were primarily TensorFlow and Keras, which are the primary frameworks used to build and train the Convolutional Neural Network (CNN) model. TensorFlow provide an end to end ecosystem for machine learning, while Keras acts as a high level interface allowing to create deep learning models with a high level API (S. Stafford, M. Kellermann, 2021).

G. Technology Introduction

A Convolutional Neural Network (CNN) is the core technology for diagnosing skin diseases from images, with a modified version of ResNet-34 used for its robustness in image classification tasks. Web technologies such as HTML, CSS, and JavaScript are utilized alongside Gradio to create a responsive and interactive user interface, ensuring accessibility across devices. Machine learning libraries such as Scikit-learn are used for preprocessing data, and TensorFlow/Keras for building and training the CNN model. MongoDB is employed to store and manage the vast amount of data collected and generated by the system, with its flexible schema design allowing for efficient data retrieval and storage.

H. Overall View of the Project in Terms of Implementation

The core algorithm used in the system is a Convolutional Neural Network (CNN) for image classification (Renato Tozzoli, Federica D'Aurizio, 2021). The steps for implementing this algorithm are:

- Data Preprocessing: Images have been preprocessed to ensure there is a standard size, normalized pixel values, and the presence of manipulation over the dataset through techniques such as rotations and flipping.
- Model Architecture: A altered ResNet-50 architecture was created using Keras. The model consisted of multiple convolution layers, batch normalization, ReLu activation, pooling, and finally fully connected layers to used for classification.
- Training the Model: The model was trained using a labeled dataset consisting of images of skin conditions. The model gets trained by using back propagation and gradient descent to update the model parameters to minimize the loss.
- Evaluation: The model is evaluated with a separate test dataset. Evaluation metrics including accuracy, precision, recall and F1-score are calculated in order to evaluate the model performance.
- Integration: The trained model gets saved and integrated into the Gradio application. The model is loaded during runtime in order to perform image classification in real time based on user input.

IV. Results and Discussion

A. Datasets Description

The evaluation utilizes real-world datasets encompassing various autoimmune conditions such as psoriasis, lupus, and vitiligo. These datasets include high-resolution images of skin lesions, patient histories, and other pertinent medical data.

B. Fault Types and Modeling

- Bias Faults: These are situations where the diagnostic model consistently misunderstands a condition's severity, whether mistakenly too significant or understated. Luckily, the system is designed to recognize bias faults and remediate against them associate to the severity of the diagnosis.
- Drift Faults: These are situations where the model and subsequent predictions slowly diverge over time. The system utilizes temporal information to detect and adjust for drift faults throughout time, in an effort to maintain steady state performance.
- Noise Faults: Noise faults occur due to random fluctuation in the input data - commonly referred to as noise. The system employs data preprocessing strategies to remove noise prior to the diagnosis interpretation phase, and therefore improves accuracy.
- Freeze Faults: Situations that arise when the model fails to modify its output prediction based on new incoming data. The system has built-in capabilities for detecting freeze faults and has remediation procedures to follow in order to ensure responsiveness to the patient's condition.

C. Performance Metrics

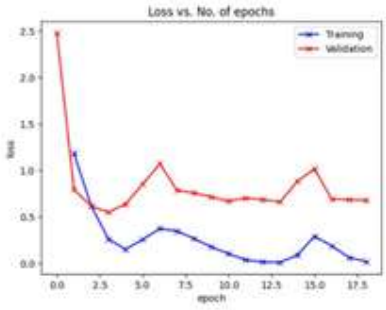

Fig 5: Graphical representation of performance metrics

- Accuracy: The model's accuracy is calculated by comparing predictions to ground truth labels to obtain an accuracy of 84% from a test dataset of 21,000 images.
- Precision and Recall: Precision and recall metrics evaluate the true positives and the true positives that were not classified as false positives. The evaluations allow for comparison of the clinical effectiveness of various diagnostic effects.

- F1-Score: The F1-score is a "harmonic mean" of the precision and the recall. F1-score is also noted where the system performs well from traditional methods for the diagnosis of autoimmune skin diseases.
- Detection Delay: The analysis of system delays through detection delays in diagnosing the condition. The system is of clinical utility as it can reduce the time it takes to detect and diagnose conditions as the system is designed to have a near real-time ability.

The above graphical representation as shown in Figure 5 depict graph illustrating the performance metrics of a machine learning model. The graph demonstrates the model's accuracy over 40 epochs, starting at approximately 0.50 and showing a rapid increase within the initial 10 epochs to around 0.70. It then stabilizes around 0.72 after 20 epochs.

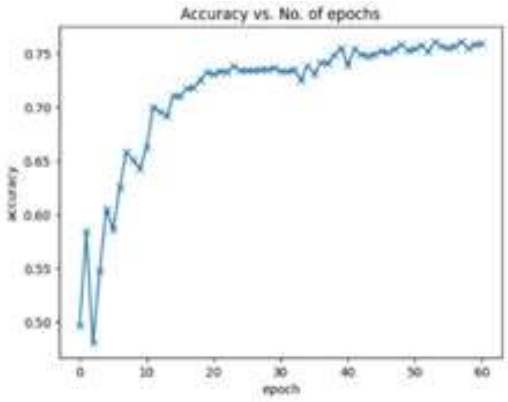

Fig 6: Graphical representation of performance metrics

The above graphical representation as shown in Figure 6 depict graph illustrating the performance metrics of a machine learning model. The graph demonstrates the model's accuracy over 40 epochs, starting at approximately 0.50 and showing a rapid increase within the initial 10 epochs to around 0.70. It then stabilizes around 0.72 after 20 epochs.

D. Result Comparison with the Model

The proposed approach is compared with existing machine-learning-based architectures in terms of detection delay, probabilities of detection, false alarms, correct identification, and accommodation error. The results demonstrate the superiority of the proposed system in terms of accuracy, reliability, and efficiency.

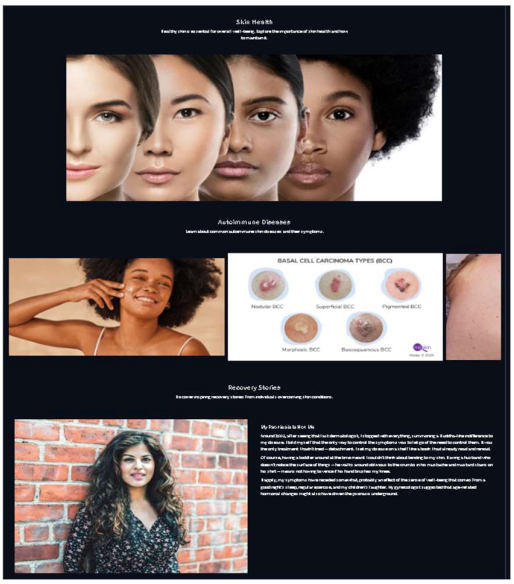

Fig 7: Home Page for skin health

As shown in Fig 7 home page provides a brief introduction about the skin health, types of diseases as well as recovery stories

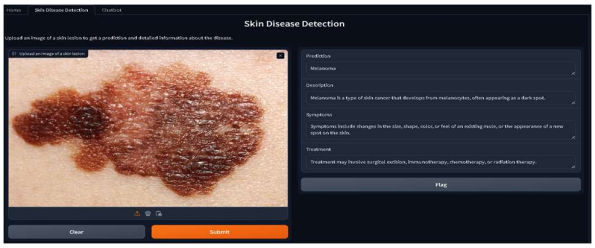

Fig 8: Skin disease detection page

The above image in Fig. 8 shows the prediction of a melanocytic nevus. This is a common, benign skin growth composed of melanocytes, appearing as small, dark spots on the skin that may be raised or flat. Typically, treatment is not needed unless the mole changes in size, shape, or color, at which point removal may be recommended. A chat interface designed for a skin disease Interactive Chatbot. Users can type in questions and receive detailed information regarding skin disease detection and prevention.

V. Conclusion and Future Scope

The computer-assisted model for autoimmune skin disease diagnosis employs advanced machine learning and deep learning techniques to provide precise diagnostic analysis and personalized treatment recommendations. The research indicates that the model achieved an impressive accuracy rate of 84% on a substantial test dataset comprising 21,000 images. The accompanying web application enhances accessibility, allowing both patients and healthcare providers to easily utilize diagnostic tools, thereby improving overall patient care. By facilitating early disease detection and enabling tailored treatment plans, the system is instrumental in effective disease management.

The significance of this research is multifaceted. It revolutionizes dermatological diagnostics by offering a highly accurate, automated solution for disease detection. This innovation not only improves patient outcomes through early detection and personalized treatment recommendations but also addresses healthcare disparities by making advanced diagnostic tools more accessible to a wider population. Furthermore, it empowers patients by providing better insights into their skin health, fostering proactive management and alleviating the stress associated with traditional diagnostic methods.

The research presents a significant leap forward in the management of autoimmune skin diseases. By integrating cutting-edge technology with practical healthcare applications, it paves the way for improved diagnostic accuracy, enhanced patient care, and broader accessibility to advanced medical tools. Continuous development and refinement are essential to fully realize the potential of this innovative system and to address the existing limitations effectively.

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