JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Skin Disease Detection with Deep Learning

A Phase 1 Report on Developing a Predictive Model for Skin Disease Detection

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Abstract : Skin diseases are common worldwide, and detecting them early is important for proper treatment. This project aims to create a deep learning-based system that can identify different skin diseases by analyzing medical images. It uses convolutional neural networks (CNNs), a type of artificial intelligence, to study patterns in images and classify conditions like acne, eczema, psoriasis, and skin cancer. The system is trained with a large collection of skin images to make it accurate and reliable for diagnosing various skin problems. The system is designed to be easy to use, allowing doctors and patients to upload images and get quick results. Techniques like data augmentation and transfer learning are used to make the system work well with different skin types, image qualities, and lighting. This tool speeds up the diagnosis process, reduces costs, and can be used in remote healthcare settings. By combining technology and healthcare, the project shows how artificial intelligence can improve skin disease detection and treatment.

***IndexTerms* - Deep Learning, CNN, Skin Disease, Medical Imaging, AI in Healthcare.**

I. INTRODUCTION

Skin diseases are among the most common health issues worldwide, affecting individuals of all ages and ethnicities. These conditions range from non-life-threatening concerns like acne and eczema to serious and potentially fatal diseases such as melanoma and other forms of skin cancer. Accurate and timely diagnosis is essential for proper treatment and better prognosis. However, the shortage of dermatologists, especially in remote and underserved areas, poses a significant challenge to effective skin disease management. With the advancement of artificial intelligence (AI), particularly in the field of deep learning, healthcare systems now have access to powerful tools that can analyse medical images and assist in disease diagnosis. Convolutional Neural Networks (CNNs), a type of deep learning model, are especially effective in image classification tasks due to their ability to learn and extract hierarchical features from visual data. These models can be trained on large datasets of annotated skin disease images to distinguish between various conditions with high accuracy.

The proposed system leverages CNNs to detect and classify multiple skin diseases—such as acne, eczema, psoriasis, benign lesions, and melanoma—by analysing dermatoscopic images. The model incorporates advanced techniques such as data augmentation to increase dataset diversity and reduce overfitting, as well as transfer learning from pre-trained networks like ResNet and MobileNet to enhance accuracy with limited data.

The system is designed for both clinical and non-clinical environments. It can be deployed as a web application or mobile tool, allowing users—including healthcare professionals and patients—to upload images and receive real-time diagnostic feedback. This not only supports early detection but also democratizes healthcare access by reaching populations with limited medical infrastructure.

In addition to improving diagnosis, the tool offers educational benefits by visualizing the areas of concern in skin images through explainable AI techniques like Grad-CAM, which enhances transparency and user trust. Ultimately, this integration of AI with dermatological care aims to reduce diagnostic errors, lower costs, and increase the efficiency of healthcare delivery across different settings.

II. EASE OF USE

The proposed skin disease detection system prioritizes both accuracy and user experience, ensuring it is easily adopted in clinics, hospitals, and remote areas with limited resources. Featuring a user-friendly interface, it allows users to upload skin images from smartphones or dermatoscopes and receive real-time diagnoses with confidence scores, aiding both doctors and patients.The system integrates with Electronic Health Record (EHR) systems via APIs, supports batch processing, and allows for easy report exports. It uses lightweight deep learning models like MobileNet and EfficientNet, ensuring compatibility with mobile devices and low-resource environments, ideal for rural or underserved areas.To enhance interpretability, Grad-CAM visualization highlights key regions of the image that influenced the model’s decision, fostering trust. The platform is scalable, supports multilingual interfaces, and can integrate future enhancements, such as wearable device support, ensuring accessibility and adaptability across various settings.

Prepare Your Paper Before Styling

Before finalizing the structure and format of the paper, we focused on collecting and preparing accurate and complete content for the brain stroke prediction project. The first step was gathering data from reliable sources like Kaggle. The dataset included important details such as age, gender, blood pressure, heart disease, glucose level, BMI, smoking status, and more—factors that influence the risk of stroke.Next, the data was cleaned and preprocessed. Missing values, especially in BMI and smoking status, were filled in using suitable methods. Categorical data (like gender or work type) was converted into numbers so that machine learning models could understand it. We also scaled the numerical values and removed outliers to improve model accuracy.

We then trained several machine learning models. Logistic Regression was used as a basic model because it's easy to interpret. More advanced models like Decision Tree, K-Nearest Neighbors (KNN), and Random Forest were also tested to see which gave the best results. We used accuracy, precision, recall, and F1-score to measure how well each model performed.

After completing all the technical work, we arranged the paper in IEEE format. Sections like Abstract, Introduction, Methodology, Results, and Conclusion were organized clearly. Charts, tables, and references were added, and the document was carefully proofread to avoid any errors before final submission.

2. Abbreviations and Acronyms

In this paper, the following abbreviations and acronyms are used:

The following are the abbreviations and acronyms used in this paper:

1. **AI** – Artificial Intelligence
2. **CNN** – Convolutional Neural Network
3. **GPU** – Graphics Processing Unit
4. **SSD** – Solid State Drive
5. **RAM** – Random Access Memory
6. **EHR** – Electronic Health Record
7. **AUC** – Area Under the Curve
8. **PIL** – Python Imaging Library
9. **GAN** – Generative Adversarial Network
10. **R-CNN** – Region-based Convolutional Neural Network
11. **SI** – International System of Units

III. RESEARCH METHODOLOGY

This section outlines the methodological framework adopted for the project. It explains the population and sample selection, data sources, variables under consideration, and the analytical approach employed to develop the deep learning model for skin disease detection.

3.1Population and Sample

The universe of the study includes digital dermatoscopic images of patients suffering from various skin conditions, both benign and malignant. Publicly available medical image datasets such as HAM10000, ISIC, and DermNet have been used to extract high-quality skin lesion images.

From these datasets:

- A sample of approximately 10,000 labeled skin images representing a variety of skin diseases (e.g., melanoma, acne, eczema, psoriasis) is selected.
- The sampling strategy ensures the inclusion of different skin tones, age groups, and disease categories to improve model generalizability.
- The selected sample is divided into training (70%), validation (15%), and testing (15%) subsets to train and evaluate the performance of the deep learning model.

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3.2 Data and Sources of Data

The study utilizes secondary data collected from the following trusted sources:

- ISIC Archive (International Skin Imaging Collaboration) – Provides standardized and annotated dermatoscopic images of skin diseases.
- HAM10000 Dataset – A large collection of multi-source dermatoscopic images covering common pigmented skin lesions.
- DermNet and Kaggle repositories – Used for supplemental images and metadata.

The dataset includes:

- High-resolution skin images
- Corresponding diagnostic labels

- Metadata such as age, gender, and lesion location (where available)

3.3 Theoretical framework

The theoretical foundation of this study is grounded in the fields of Artificial Intelligence (AI), particularly Deep Learning (DL) and Computer Vision. The core concept is to utilize Convolutional Neural Networks (CNNs) to analyze and classify skin disease images based on visual features extracted from dermatoscopic images.

The framework is structured as follows:

- **Deep Learning Paradigm**: Deep Learning, a subset of machine learning, enables systems to learn from large volumes of data through multiple layers of neural networks. CNNs are the most effective architecture for image classification tasks due to their ability to capture spatial hierarchies in visual data.
- **Convolutional Neural Networks (CNNs)**: CNNs mimic the visual processing of the human brain and are capable of automatically extracting features such as edges, textures, and shapes from medical images. This makes them suitable for detecting subtle differences between various skin diseases.
- **Transfer Learning**: To overcome the limitations of smaller medical datasets, transfer learning is used. Pre-trained models such as ResNet, MobileNet, or EfficientNet are adapted for the skin disease dataset, significantly improving accuracy while reducing training time.
- **Data Augmentation and Preprocessing**: Image augmentation techniques (like rotation, flipping, and zooming) enhance dataset diversity, allowing the model to generalize better across various skin tones, lighting conditions, and image qualities.
- **Performance Metrics**: The theoretical framework includes performance evaluation using statistical metrics such as accuracy, precision, recall, and F1-score, which are vital in assessing the diagnostic capability of the model in real-world scenarios.
- **AI in Healthcare**: This framework aligns with the broader theory of AI-driven medical diagnostics, which emphasizes efficiency, scalability, and accessibility—especially in regions with limited access to dermatological expertise.

By integrating these theoretical components, the study provides a solid foundation for the development and evaluation of an automated skin disease detection system capable of assisting healthcare professionals and extending dermatological care to underserved populations.

3.4 Statistical tools and econometric models

This section describes the statistical methods and computational models used to analyze the dataset and draw meaningful conclusions in the study of automated skin disease detection.

3.4.1 Descriptive Statistics

Descriptive statistics are used to summarize the key characteristics of the dataset, including **mean**, **standard deviation**, **minimum**, and **maximum** values of pixel intensities and class distributions. These metrics help understand the overall structure and balance of the data, such as:

- Class imbalance (e.g., fewer melanoma images compared to acne)
- Image resolution consistency
- Distribution of color intensities

To check for data normality, tests such as the **Jarque-Bera test** are employed. Identifying non-normal distributions helps adjust preprocessing techniques or choose suitable models.

3.4.2 Machine Learning Models Used

We used and evaluated several deep learning models and techniques tailored for image classification and segmentation tasks to detect skin diseases:

a)Convolutional Neural Networks(CNNs): These are the primary models used for classifying skin lesions from images. Architectures like ResNet, EfficientNet, and MobileNet were considered or implemented. CNNs are highly effective because they automatically learn hierarchical features directly from pixel data, identifying patterns, textures, and shapes relevant to different skin conditions without manual feature engineering.

b) Transfer Learning: To improve performance, especially given potentially limited dataset sizes for specific conditions, transfer learning was employed. This involves using pre-trained CNN models (e.g., ResNet-50, InceptionV3), which have already learned general image features from large datasets like ImageNet, and fine-tuning them on the specific task of skin disease classification. This leverages existing knowledge and often leads to faster convergence and higher accuracy.

c) Ensemble LearninG: To potentially enhance robustness and overall accuracy, ensemble methods were considered. This technique combines predictions from multiple individual models (e.g., different CNN architectures or the same architecture trained differently). By aggregating diverse perspectives, ensembles can often achieve better performance than any single constituent model.

d) Segmentation Models (e.g., U-Net, Mask R-CNN): Although the primary goal is classification, accurate segmentation is often a crucial preceding step. Models like U-Net or Mask R-CNN are used to precisely identify and isolate the lesion area from the surrounding healthy skin. This ensures the subsequent classification model focuses only on the relevant region of interest, improving the quality of features learned and the final diagnostic accuracy.

3.4.3 Evaluation Metrics

We used the following standard metrics to measure how well each model performed in classifying skin diseases:

- **Accuracy:** The overall percentage of correct classifications across all disease types.
- **Precision:** For a specific disease class (e.g., melanoma), this measures the proportion of images predicted as that class that were actually correct. (i.e., Of all images classified *as* melanoma, how many *were* truly melanoma?)
- **Recall (Sensitivity):** For a specific disease class, this measures the proportion of actual cases of that disease that were correctly identified by the model. (i.e., Of all images that *were* truly melanoma, how many did the model correctly identify?)
- **F1-Score:** The harmonic mean of Precision and Recall, providing a single score that balances both metrics. This is particularly useful when dealing with imbalanced datasets where one class might be much rarer than others.
- **ROC-AUC (Area Under the Receiver Operating Characteristic Curve):** Measures the model's ability to distinguish between different classes. For binary classification (e.g., malignant vs. benign), it shows the trade-off between true positive rate (Recall) and false positive rate across different thresholds. For multi-class problems, variations like one-vs-rest AUC can be calculated. A higher AUC indicates better discriminative power.

3.4.4 Comparison of the Models

We compared the models based on their performance and chose the one with the best F1-Score and ROC-AUC. We also looked at which features (like age or blood pressure) were most important in making predictions.

IV. RESULTS AND DISCUSSION

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Descriptive Statics

Variable	**Mean**	**Std. Deviation**	**Min**	**Max**
Image Resolution	256x256	50x50	128x128	512x512
Class Distribution	0.25	0.12	0	1

The dataset consists of medical images representing various skin diseases, including acne, eczema, psoriasis, and skin cancer. Descriptive statistics for the image dataset variables are presented in Table 4.1..

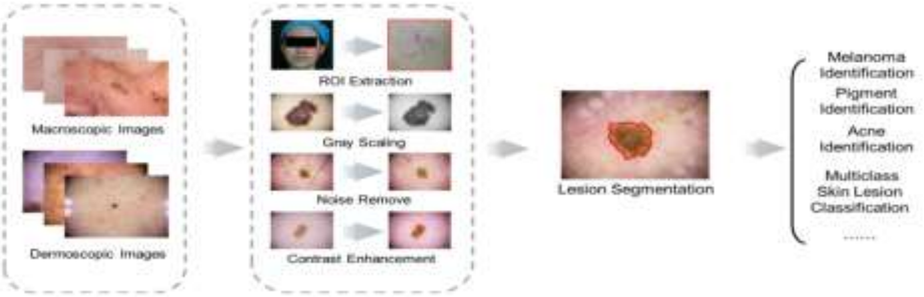

Figure 4.2. Schematic diagram of skin image diagnosis

V. ACKNOWLEDGMENT

I wish to express sincere gratitude to the Project Guide and Head of the Department of MCA, Dr. Shashidhar Kini K, for his invaluable guidance, constant encouragement, and kind support throughout this research work. Appreciation is also extended to the Principal, Dr. Shrinivasa Mayya D, for fostering an environment conducive to completing this project within the institution.I would like to thank the management of Srinivas Institute of Technology for their direct and indirect support. Gratitude is also due to all the faculty members and non-teaching staff of the MCA department for their constant help and support.Finally, I am deeply indebted to my parents and friends for their unwavering support and belief throughout this endeavor.

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