RESEARCH ARTICLE

Advancing Dermatological Care through AI: A Deep Learning-Based LINE Chatbot for Skin Disease Diagnosis

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Abstract

This paper presents the development and deployment of a LINE chatbot for diagnosing skin diseases using advanced deep learning techniques, addressing the challenge of timely and accurate diagnosis in resource-limited settings. While previous studies have explored convolutional neural networks (CNNs) for medical image classification, our research distinguishes itself by integrating MobileNetV2, DenseNet201, and EfficientNetB4 architectures within a mobile messaging platform. These CNN architectures are well-recognized for their robustness in image analysis, yet few studies have harnessed their potential in real-time diagnostic tools accessible to the general public via widely-used platforms like LINE. Our chatbot facilitates the immediate assessment of user-uploaded images, offering a proactive tool for managing skin health. By leveraging deep learning, we enhance diagnostic accuracy and reduce the reliance on traditional medical consultations. Experimental results indicate that our approach not only improves diagnosis precision but also extends the accessibility of dermatological care, particularly in underserved regions. This work contributes to the growing body of mobile health technologies by showcasing the transformative potential of AI-driven solutions in healthcare. The novelty of our research lies in the seamless integration of cutting-edge CNNs into an easy-to-use chatbot, enabling real-time, remote diagnostics in a practical, scalable manner.

1. Introduction

Skin is the largest organ of the human body, serving the important function of protecting the body from external harmful substances and preventing nutrient loss (Hameed et al., 2016). Skin diseases are influenced by various factors such as sunlight, smoking, alcohol consumption, sports, viruses, and working environment (Hameed et al., 2018). Voegeli and Hillery (2021) explore the strategies for preventing and managing moisture-associated skin damage. Their work emphasizes the importance of implementing structured skin care regimens to prevent conditions such as incontinence-associated dermatitis. According to the British Skin Foundation report in 2018, about 60% of British people suffer from skin diseases (Cork and Danby, 2017). In the United States, there are 5.4 million new cases of skin cancer annually, and one in five Americans will be diagnosed (Esteva et al., 2017). Beyond physical damage, skin diseases also have psychological effects, leading to isolation, depression, and even suicide (Picardi et al., 2013). Therefore, treating and preventing skin diseases is important in the medical field.

The general population often lacks knowledge about the types and stages of skin diseases, leading to treatment delays and allowing some diseases to progress and spread easily due to the absence of immediate symptoms. This lack of medical knowledge complicates the work of dermatologists, who often need expensive lab tests to determine the type and stage of a disease. Although advances in medical technology, such as the use of lasers and photonics devices, have proven effective in quickly and accurately detecting skin diseases, the high costs of these diagnostics prevent many people from seeking timely diagnosis.

The use of deep learning techniques to detect skin diseases has been extensively studied, with systems based on Convolutional Neural Networks (CNN) architecture introduced to classify skin diseases. These systems use various models like MobileNet, VGG19, ResNet, EfficientNet, Inception, and DenseNet to enhance diagnostic accuracy (Nath and Naskar, 2021). CNN algorithms have shown promising results in classifying and predicting various skin diseases, analyzing and processing image data to identify and categorize image characteristics (Pandey et al., 2023). This advancement has led to the development of a skin disease screening system via a LINE chatbot, which employs deep learning processes to deliver accurate results and detect skin diseases from the early stages. Users can use the LINE chatbot to check for skin diseases anytime, anywhere, saving time, reducing the need for clinic or hospital visits, reducing wait times, and lowering costs.

Contribution:

This paper presents the development and implementation of a LINE chatbot system that integrates advanced deep learning techniques for diagnosing skin diseases. By employing CNN architectures such as MobileNetV2, DenseNet201, and EfficientNetB4, this system can accurately analyze images to identify various skin diseases, providing users with a convenient tool for early diagnosis. While the system offers immediate preliminary assessments through AI-based image analysis, it is designed to assist dermatologists and credible experts by serving as an initial diagnostic aid, helping to triage cases and prioritize patient care. Although our system reduces delays and minimizes the need for in-person visits, we acknowledge that modern AI-based tools are prone to errors. Therefore, final diagnoses should always be confirmed by healthcare professionals to ensure accuracy. This approach empowers individuals by providing them with better access to medical advice while also enhancing dermatologists' ability to manage cases efficiently. Ultimately, it fosters a proactive approach to managing skin health, which can have both immediate and long-term benefits for public health outcomes.

2. Related Work

Deep learning has emerged as a valuable tool in the early and accurate detection of skin diseases (Li et al., 2020; Pandey et al., 2023; Ramamurthy et al., 2023). It offers automated computer-aided diagnosis, reducing misdiagnosis risks and labor-intensive procedures associated with traditional diagnostic methods (Gupta et al., 2023). By combining deep learning with image processing techniques, rapid and precise diagnosis of skin disorders can be achieved, potentially reducing time and cost requirements in medical settings (Pavan et al., 2023). Deep learning models, particularly convolutional neural networks (CNNs), have shown promise in extracting features from images for skin disease classification, leading to improved diagnostic precision and better treatment outcomes. The utilization of deep learning algorithms in skin disease detection presents a significant advancement in the field, enhancing the efficiency and accuracy of diagnosis processes. In addition to skin diseases, CNNs have been effectively applied in various domains. For instance, CNN-based models have been used for plant disease detection (Saisangchan et al., 2022), where lime leaves affected by different pathogens were classified with high accuracy. Similarly, nail disease detection using deep learning approaches has shown promising results, providing early and accurate diagnosis (Lapthanachai et al., 2023). These applications highlight the versatility and effectiveness of CNNs in different contexts, demonstrating their potential for broader applications in the field of healthcare and beyond.

Data augmentation techniques play a crucial role in improving the performance of deep learning models for skin recognition tasks (Alptekin and Isik, 2022). These techniques enhance the quantity and diversity of training data, especially in scenarios where labeled data is limited, such as in healthcare applications (Akrout et al., 2024). Studies have shown that generative data augmentation approaches, like text-to-image diffusion probabilistic models, can effectively generate high-quality skin images, maintaining classification accuracy even with fully synthetic datasets (Li et al., 2023). Additionally, novel methods like semantic augmentation through VAE-GAN address challenges posed by long-tailed distributions in datasets, aiding in tasks like Facial Expression Recognition (Randellini et al., 2022). By leveraging data augmentation methods involving geometrical transformations and GAN models, significant performance improvements have been achieved in facial expression recognition tasks, showcasing the importance of these techniques in enhancing model generalization.

3. Research Methodologies

This section presents the use of the 5K-Fold method to sample data and divide it into five training and validation sets. Then, the CNN models, namely MobileNetV2, DenseNet201, and EfficientNetB4, learn from these datasets. The best-performing model is used to create a LINE chatbot for more convenient consultations about skin diseases. This allows for an initial assessment through AI-based image analysis without requiring an in-person doctor's visit. The framework of the proposed method is shown in Figure 1.

The framework in Figure 1 outlines a system where users can send messages or upload images of skin conditions via the LINE Messaging API. These inputs are processed by a BOT Server, which uses Wit.AI to interpret user intent and a deep learning model to analyze the images and predict potential skin diseases. Once the image is analyzed, the model predicts the likely skin disease, and the result is sent back to the user through the LINE messaging platform, providing a preliminary diagnosis for 10 different skin conditions without requiring a doctor's visit.

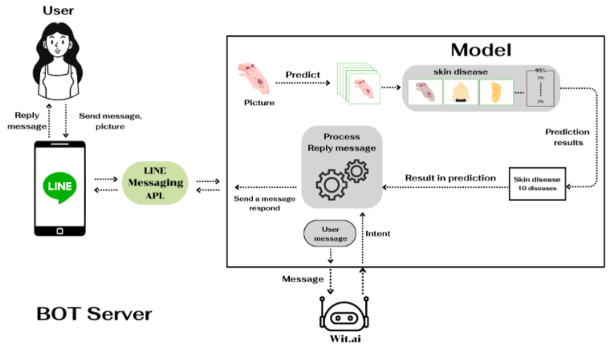

Figure 1. Framework design of DermAssist bot

3.1 Convolutional Neural Networks

3.1.1 MobileNetV2

MobileNetV2 is a lightweight deep learning architecture designed for efficient execution on mobile and embedded devices. It employs depthwise separable convolutions, significantly reducing the number of parameters and computational cost compared to standard convolutions. This architecture has been effectively used in various studies, such as differentiating between monkeypox and non-monkeypox skin lesions with high accuracy (Özaltin and Yeniay, 2023). In the classification of diabetic retinopathy, MobileNetV2 has proven effective in distinguishing different severity levels, highlighting the importance of data augmentation and fine-tuning for improved model performance (Yassin, 2023). Additionally, MobileNetV2 has demonstrated high accuracy in bird species recognition tasks, further emphasizing its versatility and efficiency in image classification through transfer learning approaches (Kondaveeti et al., 2023; Kumar and Kondaveeti, 2024). Overall, MobileNetV2's balance of performance and computational efficiency makes it suitable for a wide range of image classification tasks.

3.1.2 DenseNet201

DenseNet201 is part of the DenseNet family, known for its dense connectivity pattern where each layer receives inputs from all preceding layers and passes its own feature maps to all subsequent layers. This design alleviates the vanishing gradient problem, strengthens feature propagation, encourages feature reuse, and substantially reduces the number of parameters. DenseNet201 has been utilized in various domains, achieving high accuracy in tasks such as osteosarcoma detection (90.96%) (Salih et al., 2023) and brain tumor detection (91% during training and 88% during testing) (Sujatha and Rao, 2023). Its application extends to clothing image classification, where it enhances classification accuracy through effective feature extraction (Zhou et al., 2023), and Indian Sign Language gesture recognition, achieving remarkable accuracy (Altaf et al., 2023). DenseNet201's robust performance across different applications underscores its adaptability and high efficacy in various image classification tasks.

3.1.3 EfficientNetB4

EfficientNetB4 is part of the EfficientNet family, which scales up models in a balanced way across depth, width, and resolution using a compound scaling method. This approach allows EfficientNet models to achieve better performance with fewer parameters and floating-point operations per second (FLOPS) compared to other state-of-the-art models. EfficientNetB4 has excelled in a range of image processing tasks, including mosquito categorization (Prasher and Nelson, 2023), image captioning (Bansal et al., 2023), glaucoma classification with an accuracy of 99.38% (Albuquerque et al., 2022), and facial expression recognition with an accuracy of 94.44% (Geetha and B. Prakash, 2022). The model's efficiency and accuracy make it a reliable choice for various image-related tasks, demonstrating its versatility and effectiveness in different domains (Utami et al., 2022).

3.2 Data Augmentation Techniques

Data augmentation significantly enhances model performance by artificially increasing the size and diversity of the training dataset. This technique reduces overfitting, as it prevents the model from memorizing specific patterns in a limited dataset by introducing new variations. By applying transformations such as rotation, flipping, or zooming to existing images, the model is exposed to a wider range of possible variations of the data, improving its ability to generalize to unseen examples. This results in better accuracy and robustness of the model in real-world applications, especially when handling complex tasks such as skin disease diagnosis where the visual characteristics of diseases can vary widely across different individuals and conditions. Moreover, data augmentation helps maintain the balance of the dataset, ensuring that the model does not become biased towards certain classes with more data, which ultimately leads to improved predictive performance (Enkvetchakul et al., 2022). In this experiment, data augmentation was achieved through horizontal flip, vertical flip, rotation, and zoom.

4. Experimental Setting and Results

4.1 Dermnet Dataset

The Dermnet dataset (Aboulmira et al., 2022) consists of images of ten skin diseases conditions: Acne and Rosacea, Atopic Dermatitis, Eczema, Hair Loss, Herpes HPV, Melanoma Skin Cancer, Nail Fungus, Psoriasis, Vascular Tumors, and Warts Molluscum. As shown in Figure 2, this dataset, sourced from Kaggle, includes a total of 4,790 skin diseases images. Details are provided in Table 1.

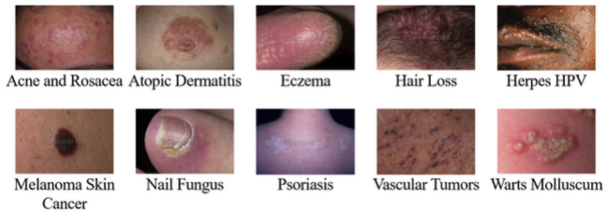

Figure 2. Illustration of the skin diseases images from the dermnet dataset.

Table 1. Details of the Dermnet dataset.

Types of Skin Diseases	No. of Images
Acne and Rosacea	474
Atopic Dermatitis	546
Eczema	455
Hair Loss	272
Herpes HPV and other STDs	464
Melanoma Skin Cancer Nevi and Moles	560
Nail Fungus and other Nail Disease	498
Psoriasis, Lichen Planus and related diseases	487
Vasculitis	573
Warts, Molluscum and other Viral Infections	464
Total	**4,790**

4.2 Experiments on Lightweight Convolutional Neural Networks

This study explored the performance of CNNs across three architectures: MobileNetV2, DenseNet201, and EfficientNetB4. Data augmentation techniques, including rotation, zoom, vertical flip, and horizontal flip, were applied to a skin disease dataset encompassing 10 classes and 4,790 images. The dataset was divided into training (80% or 3,832 images) and test sets (20% or 958 images). The training set was further partitioned via 5-fold cross-validation into 80% (3,065 images) for training and 20% (766 images) for validation. Models pre-trained on the ImageNet dataset were fine-tuned using these partitions and augmented data. Experimental results, as presented in Table 2.

Table 2. The effect of data augmentation on the performance of these three architectures.

CNN Architectures	Original Image		Data Augmentation	
	5-CV (%)	Test (%)	5-CV (%)	Test (%)
MobileNetV2	52.77±0.91	53.91	58.83±1.14	60.38
DenseNet201	81.35±0.61	80.50	81.97±1.31	82.01
EfficientNetB4	75.01±1.64	58.19	76.56±1.55	77.69

From table 2, a comparison of the CNN architectures (MobileNetV2, DenseNet201, and EfficientNetB4) reveals that data augmentation significantly enhances the performance of all three models, particularly for MobileNetV2 and EfficientNetB4. For MobileNetV2, data augmentation increased validation accuracy from 52.77% to 58.83% and test accuracy from 53.91% to 60.38%. Similarly, EfficientNetB4 saw its test accuracy surge from 58.19% to 77.69% after augmentation. DenseNet201 consistently achieved the highest performance across the board, with a test accuracy of 80.50% without augmentation and 82.01% with it. This shows that while DenseNet201 remains robust, data augmentation improves the results even further, particularly for models like MobileNetV2 and EfficientNetB4 that initially perform at lower accuracy levels. To determine which areas of an image are crucial for model predictions, we employed Gradient-weighted Class Activation Mapping (Grad-CAM) on images of different skin conditions. This method analyzes the regions of the image that have the most impact on the model's decision-making process in classifying diseases, shown in Figure 3.

To evaluate the performance of the CNN models, we generated confusion matrices for the classification of skin diseases. The confusion matrix provides a detailed breakdown of the model's predictions, indicating the true positive, false positive, true negative, and false negative rates for each category. This allows for a comprehensive understanding of the model's accuracy and areas where it may need improvement. Figure 4 below shows the confusion matrix for our model, illustrating the classification results across different skin disease categories. As seen, the model achieves high accuracy in categories such as Nail Fungus and Melanoma Skin Cancer, while there are some misclassifications in categories like Atopic Dermatitis and Vascular Tumors.

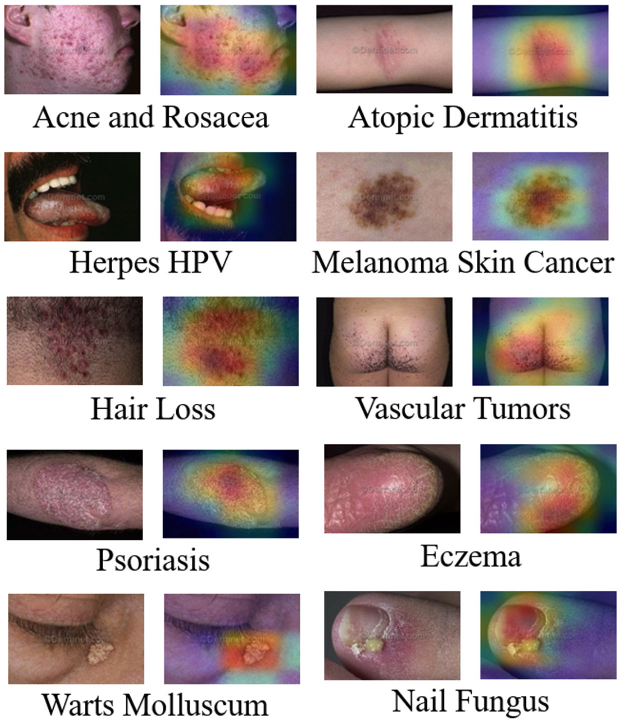

Figure 3. Grad-CAM visualization of skin disease images.

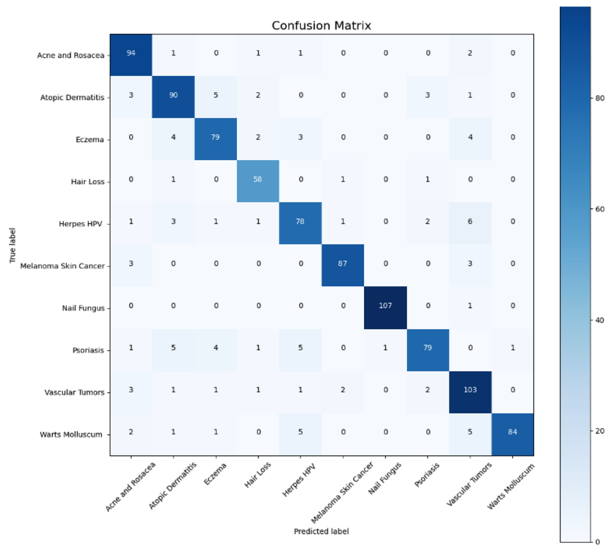

Figure 4. Confusion matrix for skin disease classification.

4.3 User Interface Screens of DermAssist Bot

Here are examples of interface screens from a chatbot designed using a diagnostic model for skin diseases. Figure 5a is the chatbot's home screen which displays the logo and various menu options. Figure 5b shows the chatbot's welcome message, where it expresses gratitude to users for adding it as a friend. Figure 5c offers detailed information about different skin conditions, such as atopic dermatitis and acne, helping users understand these diseases better. Figure 5d serves as a user manual, guiding users on how to interact effectively with the chatbot. Figure 5e presents a practical example where the chatbot responds to a query regarding the likelihood of having acne or rosacea, providing a calculated probability. This system enhances user accessibility to vital information and guidance on skin conditions, facilitated through automated chatbot interactions.

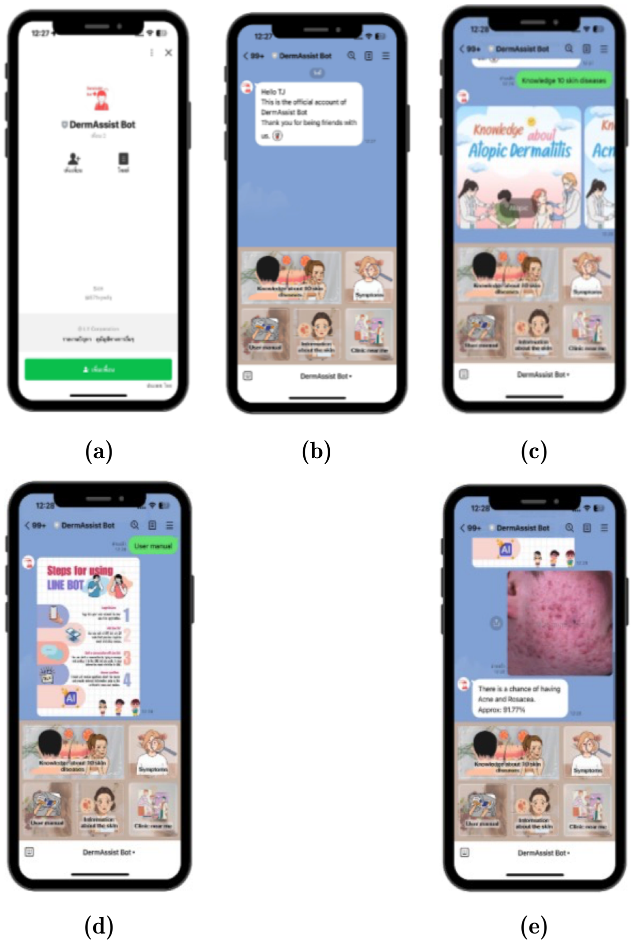

Figure 5. Screenshots of DermAssist bot interface.

5. Discussion

The results of this research indicate that the integration of advanced deep learning models within a LINE chatbot interface offers a promising approach to skin disease diagnosis. The use of CNN architectures such as MobileNetV2, DenseNet201, and EfficientNetB4 has shown significant improvements in diagnostic accuracy, particularly when data augmentation techniques are applied. The chatbot's ability to provide immediate preliminary assessments reduces the dependency on in-person medical consultations, which is especially beneficial in resource-limited settings.

One of the key advantages of the proposed system is its accessibility. By leveraging the popular LINE messaging platform, the chatbot reaches a broad audience, making it a convenient tool for users to manage their skin health proactively. This approach not only enhances diagnostic accuracy but also democratizes access to dermatological care, potentially leading to earlier detection and treatment of skin conditions.

However, there are limitations to consider. The performance of the models is heavily reliant on the quality and diversity of the training data. Although data augmentation techniques help mitigate this issue, further efforts are needed to expand the dataset with more diverse and representative images of skin diseases. Additionally, while the chatbot provides valuable preliminary assessments, it is not a substitute for professional medical advice. Users should be encouraged to seek consultation with healthcare providers for definitive diagnoses and treatments.

Future work should focus on addressing these limitations by expanding the dataset, exploring newer deep learning models, and incorporating multi-modal data for a more comprehensive diagnostic approach. Real-world deployment and validation through large-scale user studies will be crucial to assess the chatbot's impact on patient outcomes and healthcare delivery.

6. Conclusions

This research marks a notable advancement in employing deep learning technologies for skin disease diagnosis through a LINE chatbot interface. Utilizing state-of-the-art convolutional neural networks (CNNs) such as MobileNetV2, DenseNet201, and EfficientNetB4, the system improves diagnostic accuracy and enhances access to medical consultations, thus democratizing expert healthcare advice. The LINE chatbot, equipped with advanced image processing and machine learning capabilities, delivers effective preliminary assessments of skin conditions on mobile devices, reducing the necessity for in-person clinic visits often limited by time, cost, and geographical barriers. This quick and reliable health assessment can have a substantial impact on public health by facilitating earlier detection and treatment of skin diseases, potentially mitigating their progression and severity.

CRediT Authorship Contribution Statement

Prem Enkvetchakul: Conceptualization, Methodology, Software Development, Formal Analysis, Investigation, Data Curation, Visualization, Writing – Original Draft. **Waranya Chawooram:** Software Development, Validation, Investigation, Data Curation, Writing – Review & Editing. **Adisorn Pluempan:** Methodology, Software Development, Formal Analysis, Validation, Writing – Review & Editing. **Sangdaow Noppitak:** Conceptualization, Methodology, Supervision, Project Administration, Writing – Review & Editing, Funding Acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of AI Use

The authors declare that this manuscript includes content generated or assisted by artificial intelligence (AI) tools. Specifically, AI tools were employed to support language editing. All AI-assisted content was critically reviewed, verified, and approved by the authors to ensure accuracy, originality, and compliance with ethical standards.

Data Availability

The data supporting the findings of this study are publicly available on Hugging Face at `https://huggingface.co/datasets/exper1ment/dermnet`.

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