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A Hybrid CNN - Rule-Based Classifier Skin Infection Determination Model

EZUKUSE, B. G.[1], AKAZUE, M. I.[2]
[1, 2]Department of Computer Science, Delta State University, Abraka, Nigeria

Abstract-* Skin infections are affecting millions of individuals across all age groups and significantly impacting quality of life because of climate change and other factors. Skin infections can be on any part of the human body. It usually occurs on the back head, Lip, foot, lap, leg, hand, and so on. These infections can be discomforting and embarrassing to the individual. Therefore, early detection is crucial for effective treatment, inhibition of disease development, and minimizing psychosocial effects. This paper evaluates the use of different machine learning techniques by different authors by using document review and site visit. The results obtained, methodology applied, system analysis and design tools were the factors and metrics used for evaluation. It concludes that a hybridized CNN Rule-based classifier is a better model for skin infection determination in the developing countries. The paper recommends the implementation of this model for healthcare givers.

I. INTRODUCTION

Recent progress in machine learning, especially in image-based classification techniques, has demonstrated strong potential in automatically identifying complex patterns in skin images, differentiating between benign and malignant lesions, and enabling early disease detection (Karimkhani et al., 2017; Ojie et al, 2023; Okpor et al 2024a; Okofu et al 2024b; Mega et al. 2024). In skin disease determination, the machine algorithms enhance diagnostic accuracy, reduce variability caused by human assessment, and provide scalable solutions for regions with limited access to dermatologists. By training on extensive image datasets, machine learning algorithms improve prediction performance and patient outcomes (Idiodi et al 2025; Oboro, and Akazue 2025; Aghware et al 2025; Okofu et al 2024a; Okpor et al. 2024b; Akazue et al 2024).

Transparency and explainability are becoming a more popular concept as machine learning models become more prevalent in healthcare. Explainable AI (XAI) methods are in the process of development to contribute to a deeper understanding of how models are formed to make decisions, the knowledge of which is essential to earn the trust of both medical workers and patients (Holzinger et al., 2019). Other recent methods of visualization like Gradient-weighted Class Activation Mapping (Grad-CAM) and Layer-wise Relevance Propagation (LRP) have been proposed to emphasize certain areas of an image that the model used to make a prediction, thus making diagnostic decisions more comprehensible to clinicians (Samek et al., 2022).

Although these have been developed, there are still a number of issues. ML models can be affected by variability in image quality, variation in lighting conditions, and artifacts. Image rotation, cropping, and normalization are examples of data augmentation methods that are increasingly deployed to solve these problems through increasing the diversity of a dataset and making the model more resistant (Wibowo, 2024). Moreover, the issue of the ethical consideration such as privacy of the data, the possible bias of the algorithms, and the necessity of the regulatory approval should be considered to guarantee the safety and efficacy of the deployment (Char et al., 2018). In particular, algorithmic bias is a major threat when the models are trained on a non-demographically diverse dataset, which may decrease the accuracy for the underrepresented groups. To resolve such issues, it is necessary to consider the technical solutions that adheres to international health data standards (Kumar et al, 2024).

1.1 Machine Learning

Machine Learning (ML) has become essential in healthcare for automating diagnosis and enhancing decision-making (Zhang et al., 2023). Recent advances in deep learning and neural networks have enhanced disease prediction and medical imaging analysis (Wibowo, 2024). There are three main types of machine learning algorithms: supervised, unsupervised, and reinforcement learning. Each type has its own purpose. (Smith et al., 2023).

1.1.1 Categories of Machine Learning

Support Vector Machines are supervised learning methods that are used for both classification and regression. They find the best line that separates different groups in a dataset. Recent enhancements have augmented their precision and efficacy in practical applications (Zhang et al., 2023; Ojugo and Yoro, 2021; Akazue et al., 2024c). Random Forest is good at working with complicated data and stopping overfitting. Recent studies underscore its efficacy in medical diagnosis, fraud detection, and market analysis (Wibowo, 2024). For example, Random Forest has been utilized in breast cancer prediction, demonstrating strong classification performance on medical imaging datasets (Abdar et al., 2021; Ajenaghughrure et al., 2017; Aghware et al., 2025; Ako et al., 2024).

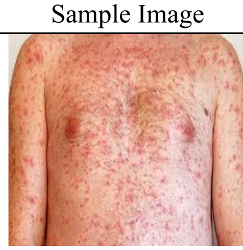
KNN is a simple but effective way to classify data. It gives labels based on the majority class of the k closest data points. It needs to store a lot of data, but it has worked well in many areas, including recommendation systems and image recognition (Wainer, 2016). One important use of KNN is in handwriting recognition, where it can correctly identify handwritten numbers in the MNIST dataset (LeCun et al., 1998). Naïve Bayes is a classification model that uses probabilities and assumes that features are not related to each other. Even though it's simple, it works great for text classification, spam filtering, and sentiment analysis. Recent studies (Wibowo, 2024; Metsis et al., 2006; Ojeme & Mbogho, 2016; Ojugo & Otakore, 2020) compare its accuracy to that of other models in finding false information.

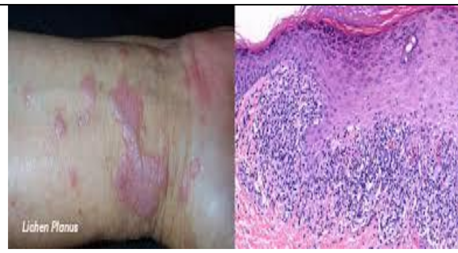
PCA is a method for reducing the number of dimensions that is often used in data visualization, image processing, and financial modeling to make calculations faster (Smith et al., 2023; Ringnér, 2008). K-Means is an unsupervised clustering algorithm used for customer segmentation, anomaly detection, and biological data classification (Brown & Liu, 2022; Jain, 2010). Gradient Boosting is a sequential learning method that improves predictions by correcting errors from earlier iterations. XGBoost, LightGBM, and CatBoost are more advanced versions that have made processing faster and more accurate. They are widely used in structured data analysis and predictive modeling (Chen & Guestrin, 2016; Aghware et al, 2025; Ako et al., 2024; Nayak et al., 2021).

1.2 Skin Diseases

Skin diseases can cause a wide range of symptoms, from mild irritations to serious chronic diseases. Recent advancements have enhanced their treatments; however, challenges persist in early detection and diagnosis. Kumar et al. (2024) assert that the integration of machine learning with clinical practice provides solutions for enhancing the management of skin diseases. Table 1 shows how different kinds of skin diseases are grouped and explained.

Table 1: Categories of Skin Diseases with Sample Images

Category	Sample Image	Description
Infectious Skin Diseases		Caused by bacteria, fungi, viruses, or parasite. Examples are impetigo, herpes simplex, ringworm, scabies (Brown, 2020).

Inflammatory Skin Diseases		Characterized by inflammation, redness, and itching. Examples: Psoriasis, Eczema, Rosacea response (Boehncke and Schön, 2015).
Genetic Skin Disorders		Inherited skin conditions caused by gene mutations. Examples: Epidermolysis bullosa, Ichthyosis (Oji and Tadini, 2015).
Auto immune Skin Diseases		Occur when the immune system attacks healthy skin cells. Example are Lupus erythematosus which causes inflammation and vitiligo which leads to loss of skin pigmentation (Robinson and Rosenbaum, 2020).
Neoplastic Skin Diseases		It includes benign and malignant tumors. Examples are melanoma, basal cell carcinoma, and squamous cell carcinoma (Apalla et al., 2017).
Allergic Skin Diseases		Triggered by allergens such as foods, chemicals, or medications. Examples: Contact dermatitis, Urticaria (hives) (Johansen et al., 2015).

1.2.1 Causes of Skin Disease
1.2.1 Causes of Skin Disease
Skin diseases arise from various factors, ranging from infections and genetic predispositions to environmental exposures and immune system malfunctions. Each type of cause can lead to a wide array of skin conditions, influencing their severity, symptoms, and treatment options.

i. Infectious Agents: Infectious agents such as bacteria, viruses, fungi, and parasites are significant causes of skin diseases. Bacterial infections like cellulitis and impetigo are commonly caused by Staphylococcus aureus and Streptococcus pyogenes, which can enter the skin through cuts or abrasions, leading to infection (Ladhani, 2018). Viral infections such as herpes simplex virus (HSV) cause cold sores and genital herpes, while human papillomavirus (HPV) leads to warts. Molluscum contagiosum, caused by a poxvirus, is another common viral skin infection (Al-Sheikh, 2020). Fungal infections like athlete's foot, ringworm, and candidiasis are caused by dermatophytes, Candida species, and other fungi that thrive in warm, moist environments (Ameen, 2010). Parasitic skin illnesses, such as scabies caused by the mite Sarcoptes scabiei and lice infestations, are caused by parasitic organisms that live on or inside the skin (Chosidow, 2012).

ii. Genetic Factors: Mutations or hereditary factors play a major part in the genetic basis of many skin diseases. Genetic factors contribute to conditions including epidermolysis bullosa, which causes fragile skin that blisters easily, and ichthyosis, which is characterized by dry, scaly skin (Oji and Tadini, 2015). These genetic conditions can have a major impact on a person's quality of life and frequently appear early in life. Research keeps identifying the precise genetic alterations at play, which advances knowledge and may lead to gene-targeted treatments.

iii. Immune System Problems: Autoimmune diseases happen when the immune system attacks the body's own tissues, which can cause skin diseases. Lupus erythematosus, in which the immune system attacks the skin and other organs, and vitiligo, which destroys melanocytes and causes patches of skin to lose color, are two well-known examples (Robinson and Rosenbaum, 2020). These conditions underscore the intricate interplay between the immune system and the skin, frequently necessitating specialized interventions to regulate the immune response and alleviate symptoms.

iv. Allergic Reactions: Skin disorders like atopic dermatitis (eczema) and allergic contact dermatitis can be brought on by allergic reactions. According to Johansen et al. (2015), these reactions are frequently brought on by exposure to allergens such as nickel, latex, and specific cosmetics, which trigger an immune response that results in skin irritation and inflammation. The quality of life is greatly impacted by atopic dermatitis, which is caused by both genetic and environmental factors and is characterized by persistent, recurrent skin inflammation and severe itching.

v. Environmental Factors: Sunburn, early aging, and an increased risk of skin cancers like melanoma are all known consequences of prolonged exposure to ultraviolet (UV) radiation from the sun (Apalla et al., 2017). Contact dermatitis and occupational skin diseases are among the skin conditions that can result from chemical exposures, such as contact with irritants or pollutants. Preventive measures and lifestyle modifications are necessary because environmental factors are important in the development and aggravation of skin diseases.

vi. Hormonal Changes: Hormones play a great role in skin health, and acne is often associated with hormonal changes during puberty, pregnancy or menstruation. Hormonal changes can also lead to skin problems, including melasma (the condition of hyper pigmented patches) and hirsutism (excessive hair growth) (Zaenglein et al., 2016). There is a need to understand how hormones affect the skin and influence each of these conditions so developers can create targeted treatments.

vii. Lifestyle Factors: Diet, Stress and Hygiene Practices — These are lifestyle factors that are important for skin health. Bad nutrition, too much stress and not enough care for skin can lead to recurrent or new skin problems. We know smoking and excessive alcohol consumption are also known to have a deleterious effect on skin health, contributing toward premature aging and other dermatopathologies (Dreno et al., 2018). Many skin diseases can be managed and prevented through lifestyle modifications.

viii. Medications and Medical Treatments: Certain medications and medical treatments can sometimes affect the skin in unwanted ways. For instance, drugs such as antibiotics, anti-epileptic medications, and chemotherapy agents may trigger reactions like skin rashes, increased sensitivity to sunlight, or conditions such as drug-induced lupus. In addition, cancer treatments like radiation therapy can irritate the skin and cause a condition known as radiation dermatitis, which often appears as redness, dryness, and inflammation of the affected area (Sivamani et al., 2009). Being aware of these possible skin-related side effects is important, as it helps healthcare

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providers and patients recognize symptoms early and manage them effectively.

1.3 Overview of Machine Learning

Machine Learning (ML) is a subset of Artificial Intelligence (AI) with a focus on developing ML algorithms with the ability to learn from and make decisions based on available data. ML algorithms have the ability to recognize patterns in available data and have the capacity to learn from the available data. It is because of these characteristics that ML is considered a powerful tool (Zhou et al., 2024).

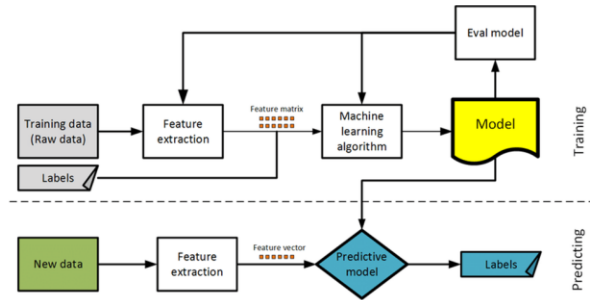
1.3.1 Types of Machine Learning

According to Ismail (2024), there are three (3) major types of machine learning which includes;

i. Supervised Learning
ii. Unsupervised Learning
iii. Reinforcement Learning

Supervised Learning

The process of supervised learning happens when a model is trained with a labeled dataset. In the process of supervised learning, a set of examples in the training data is associated with a particular output label. The main aim of the supervised learning process is to accurately predict the output or value of new examples of data. Supervised learning can be classified into two processes: classification and regression. Some of the supervised machine learning models include Linear Regression, Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Neural Networks. These models learn from the data in an iterative manner and update their parameters in a manner that minimizes the error in the prediction results, hence improving their accuracy: Figure 1 (Zhou et al., 2024).



Unsupervised Learning
Unlike supervised learning, unsupervised learning does not use a labeled response in the training process. It focuses on finding hidden patterns or structures in the input data. Unsupervised learning can be used in exploratory data analysis, where the aim of the analysis is to understand the relationships in the given data. Unsupervised learning tasks include clustering and association. In clustering, the data points are grouped together based on the features of the data. It can be used in customer segmentation and market analysis using clustering algorithms like K-means and Hierarchical Clustering. Association methods, including the Apriori Algorithm, find rules that describe a large portion of the data and can be used in applications such as recommendation systems and market basket analysis. Principal Component Analysis (PCA) is another method used in unsupervised learning. It helps in reducing the dimensionality of the data, making it easier to visualize. Figure2 indicates that unsupervised learning helps in gaining insights and new information by finding the hidden patterns and relationships in the data.

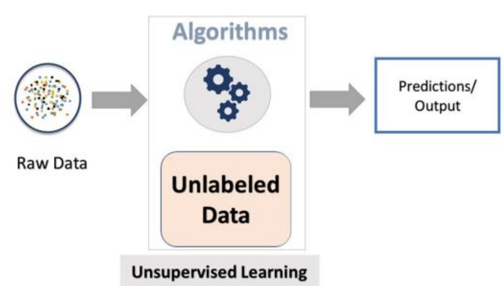


Figure 2: Unsupervised Machine Learning (Zhou et al., 2024)

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Reinforcement Learning

Reinforcement learning is a machine learning technique in which an agent seeks to learn a decision-making policy through interacting with an environment. The agent receives feedback in the form of rewards or penalties based on the decisions it makes. It seeks to maximize the reward over time. Reinforcement learning was motivated by behavioral psychology in which an agent seeks to learn from the consequences of its actions. It is a suitable technique in situations where decisions are made sequentially with delayed consequences. Reinforcement learning is used in game playing, robotics, and autonomous vehicles. The techniques used in reinforcement learning are Q-Learning, Deep Q Networks (DQN), State-Action-Reward-State-Action (SARSA), and Policy Gradient Methods. These techniques help the agent develop a strategy or policy based on which decisions are made in a particular environment. These decisions are based on the states of the environment. Reinforcement learning techniques help the agent learn through interacting with the environment. It improves its decisions over time.

II. REVIEW OF RELATED RESEARCH WORK

The study conducted by Sun et al., (2023) collated and analyzed the applications of ML in the field of skin lesion research. The aim of the study was to promote the development of automated systems for the diagnosis of skin disease. The study summarized and reviewed various research articles that were published mainly after 2013. The study focused on the contribution, method, and result of ML and DL in the recognition of skin disease. The study concluded that ML and DL have made significant contributions to the recognition of skin disease. The study concluded that the research will soon lead to the adoption of the automated diagnosis system.

Adarsh et al., (2023) described a method for classifying skin diseases using convolutional neural networks and the HAM-10000 dataset. This method for classifying skin conditions uses CNN for the analysis and classification of the conditions. This method is based on the use of the HAM-10000 dataset. This method was intended for the classification of various types of skin conditions, including nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular, and dermatofibroma. This research provided a more efficient method for the diagnosis of conditions, allowing for a quicker and more effective treatment for the patient. However, the use of the HAM-10000 dataset and the methodology provided by the research underscored its originality.

Ray & Choudhury (2021) concentrated on the application of deep learning techniques in automatic skin disease detection. The authors used a deep neural network (DNN) architecture in the classification of various skin diseases based on the visual features of the images. The findings of the research indicated that DNNs presented promising results in the automatic detection of skin diseases, especially in distinguishing between various diseases. However, the research had a challenge of ensuring high accuracy with small datasets and the need for large datasets. The authors of the research recommended the use of advanced techniques in data augmentation and the use of DNNs in conjunction with other machine learning models, such as SVMs.

Rehman et al., (2020) focused on the use of various machine learning algorithms for skin disease diagnosis. The study used decision trees, SVMs, and k-nearest neighbors (KNN) to classify skin lesions based on features extracted from medical images. Preprocessing included color feature extraction, texture analysis, and feature scaling to improve classification accuracy. Findings showed that SVMs achieved the highest accuracy compared to other classifiers. However, the study acknowledged challenges such as feature extraction complexity, limited annotated data, and model interpretability. The authors emphasized the importance of data augmentation techniques, such as rotation and flipping, to expand the dataset and improve model robustness.

Riaz & Nasrullah (2022) presented a comprehensive study that reviewed the different deep learning techniques that are being used for the detection of skin diseases. The authors discussed the different techniques, including CNN, RNN, and hybrid techniques. They analyzed the performance of the techniques in the detection of skin diseases. The authors discussed the importance of transfer learning using pre-trained models such as VGGNet to avoid the challenges associated with the availability of limited data. The study revealed that the performance of the CNN technique outperformed the performance of other machine learning techniques in terms of the accuracy of the classification. The challenges associated with the technique include the availability of a large dataset and the problem of overfitting when the dataset is small.

Rizwan et al., (2020) examined a study that sought to develop a prediction system for skin diseases using deep learning. The authors employed CNNs in the classification of different skin diseases, with a focus on melanoma and other skin diseases. The preprocessing techniques employed were the removal of noise and enhancement of the features of the images to improve the prediction of the skin diseases. The study revealed that CNNs were better than decision trees and SVM in attaining high accuracy. However, the study cited the challenges that exist in the development of a prediction system for skin diseases. These include the need for large datasets and the computational cost.

Ryu et al., (2021) studied and focused on the use of machine learning models in the prediction of the severity of skin diseases such as eczema and psoriasis. The purpose of the study was to assist in the planning of the treatment of the respective diseases. The study was conducted using supervised learning techniques and CNNs. Feature extraction was conducted using image and clinical data. The study concluded that the use of machine learning models could be effective in the prediction of the severity of the respective diseases. This could assist dermatologists in the decision-making of the respective treatments. However, the study noted that the availability of clinical data was limited, especially on less common skin diseases. The study recommended that future research should be conducted on the use of multi-modal learning in the prediction of the respective diseases.

A hybrid approach was proposed by Sahu & Das (2023) that incorporated image processing techniques along with CNNs for prediction as well as classification of skin diseases. The proposed approach showed high classification accuracy for skin diseases such as acne and eczema. The results indicate that by incorporating image processing techniques along with deep learning models, it is possible to enhance the generalization capability of the model for various images of skin diseases. However, it is important to note that there are challenges that are associated with this approach, such as the availability of data as well as overfitting.

The paper by Parisi et al., (2019) emphasized strategies that can be employed to ensure that neural networks are able to adapt to new situations while at the same time remembering previously learned experiences. This is a very important consideration for dynamic areas like skin diseases. The paper emphasized strategies like elastic weight consolidation, progressive neural networks, and generative replay as potential solutions to mitigate forgetting. The findings emphasized the potential of such strategies for dynamic systems that require adaptation while at the same time remembering previously learned experiences.

PMK et al., (2023) proposed a solution for early detection and classification of skin diseases by analyzing images using a combination of traditional image processing techniques and machine learning models like SVMs and CNNs. The preprocessing of images was achieved by enhancing contrast and removing noise from images. The findings emphasized that CNNs are more effective than traditional classifiers in achieving better accuracy for detecting diseases like eczema and psoriasis. The challenges emphasized by this paper are related to variations in image quality and availability of datasets. The paper also emphasized the need for real-time capabilities.

In the article by Pomeranz & Walden (2020), the author discussed the applications of different AI models, including CNN and deep generative adversarial networks (GAN), for lesion detection, segmentation, and disease classification. With regard to the methodological aspect of the study, the author prominently discussed the concept of transfer learning and how it could enhance the performance of the AI model despite the scarcity of data. The findings of the study revealed the efficacy of AI in attaining higher accuracy than humans in the field of dermatology, particularly in the detection of melanoma.

Prasad & Agrawal (2022) performed a comparative study to compare the efficacy of different deep learning models in the detection of melanoma and non-melanoma skin cancers. The authors employed pre-trained CNN architectures including Res Net and VGG Net. They applied the concept of transfer learning to the pre-trained models. The findings of the study revealed the efficacy of Res Net in attaining higher accuracy in the detection of melanoma due to the deep architecture of the network. However, the challenges include the occurrence of overfitting due to the scarcity of data and the computational complexity of the deep network.

Rakhimov et al., (2023) conducted a research that analyzed the use of CNNs for effective classification of various skin diseases. The research adopted a multi-class classification approach by utilizing a customized CNN that was fine-tuned using a large dataset of dermoscopy images. The research employed various techniques, such as advanced preprocessing strategies like color normalization and enhancement of features, to handle various input data. The results showed that CNNs are effective in achieving accuracy and robustness, especially for differentiating between benign and malignant diseases. However, it is a challenge to deal with data imbalances as well as computational requirements for real-time processing. The research suggests that incorporating ensemble learning as well as federated learning is necessary to enhance accuracy while considering data privacy.

Hongfeng et al., (2020) analyzed various research and approaches undertaken to date. The focus is on the methodologies adopted, challenges encountered, and the success achieved. The challenges faced in addressing interpretability and transparency in deep learning-based clinical applications and effectively integrating deep learning systems into clinical workflow and practice are major hurdles. The article concludes on a positive note regarding the future scope and prospects of deep learning in revolutionizing skin disease diagnosis.

Salehahmadi and Kalantari (2021) discussed various machine learning techniques such as decision tree, support vector machine (SVM), and convolution neural networks (CNN), and their application in classifying skin diseases. The authors highlighted that CNN is particularly useful in detecting skin diseases by its ability to recognize features from images of skin lesions. The authors highlighted some of the challenges associated with machine learning techniques such as data imbalance, requirement of large datasets for training these models, and overtraining these models. The authors were of the opinion that integration of multi-modal data such as clinical data along with images could be useful in detecting diseases. Additionally, the authors highlighted that research is required to be undertaken to improve interpretability through explainable AI techniques.

Sharma & Verma (2020) emphasized their research work on the application of CNNs for automatic prediction of skin diseases. The research work utilized a huge dataset of skin images and employed different architectures of CNNs like LeNet, Alex Net, and VGG Net for classification of various skin diseases like melanoma, psoriasis, and eczema. The results of the research work revealed that CNNs are more effective compared to traditional classifiers like k-NN and SVM in terms of classification accuracy for skin diseases. The research work also emphasized the advantages of transfer learning for better results despite the challenges that come from a lack of labeled data.

The research conducted by Siddiqui and Malik (2022) was focused on the detection of skin cancer using deep learning models. The researchers proposed the use of a hybrid approach that integrated CNNs and image processing techniques for the classification of skin lesions as benign and malignant. The dataset that was used for the training of the proposed model was based on the use of dermoscopic images of the skin. During the pre-processing of the images, the researchers proposed the use of color normalization and edge detection techniques. The proposed model was effective in the detection of malignant skin lesions using CNNs compared to the use of traditional machine learning algorithms such as SVM and decision tree. However, the challenges that were associated with the proposed model were the availability of large datasets and the computationally intensive nature of the proposed model.

The advantage and disadvantage of using traditional algorithms such as k-NN, decision trees, SVMs, and deep learning techniques such as CNNs have been discussed in the research work conducted by Singh et al., (2021). It was found that CNNs have shown promising results in the classification of skin diseases. However, problems associated with the need for high-quality and large-scale datasets and class imbalance are still major problems in machine learning techniques. Various techniques have been discussed in the research work conducted by Singh et al., (2021) in overcoming these problems. It was also found that machine learning techniques have the potential to improve the accuracy of the results in the diagnosis of skin diseases.

Smith and Green (2023) discussed and highlighted the application of deep learning methods for skin diseases' prediction. The authors discussed various deep learning architectures used in dermatological image classification tasks. These include CNNs, RNNs, and hybrid approaches. The advantages of CNNs were highlighted in the study. These include the ability to automatically learn features from images without requiring feature engineering. The study's findings showed that deep learning methods, especially CNNs, outperform traditional machine learning methods such as SVMs and decision trees in skin diseases classification tasks with high accuracy. However, some challenges were highlighted in the study. These include the availability of labeled datasets and overfitting and interpretability issues associated with deep learning methods.

In another study, Srivastava and Mishra (2021) integrated CNN and LSTM for the prediction of skin diseases. This study also capitalized on the advantages of both architectures. CNN was used for the prediction of images, while LSTM was used for the prediction of sequential data. Images were used in the dataset for the training of the model. High accuracy was recorded in the classification of various types of skin diseases. Among the findings was the capability of the model to generalize well, especially when dealing with small datasets. Among the challenges encountered in the study was the computational complexity and the requirement for large datasets.

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An Artificial Intelligence-based mobile application has been developed by Maduranga et al., (2022) for identifying different types of skin diseases. Deep learning algorithms like CNN are used in skin disease classification due to their high efficiency in image recognition. A detailed review of research articles on methods of identifying objects was conducted, comparing their efficiency in identifying skin diseases. CNN-based methods have been identified as the most efficient method in identifying skin diseases. One of the biggest challenges in making sure that the HAM10000 dataset is representative and diverse enough to encompass all skin diseases is a significant challenge. It has been revealed that MobileNet with transfer learning has an accuracy rate of about 85%, making it an efficient model in identifying skin diseases automatically.

A simple and rapid method for detecting skin disease was developed by Nawal in 2019. This method uses simple hardware, such as a camera and a computer. Image input for the system is the input of color images of the affected area on the skin. Image processing for the system is the resizing of images and feeding them into a trained CNN. This system was successful in detecting three types of skin disease with a high accuracy rate of 100%.

The study by Su et al., in 2020, on the efficacy of deep learning in detecting skin disease highlighted the efficiency of deep learning in detecting characteristics such as the boundary, color, and texture of the lesion, which are significant for diagnosis. CNN was also found to be more effective than other machine learning techniques, especially in terms of accuracy and speed. However, the study also highlighted some challenges, such as the absence of datasets and the requirement for large datasets for training the model. Additionally, the difficulty in generalizing the model for different people with different skin tones and textures was also identified.
Tan & Liew (2021) compared the performance of different architectures of CNNs, including VGG16, ResNet, and InceptionV3, in terms of the performance of the models in classifying different skin diseases such as melanoma, eczema, and psoriasis. The study revealed that the performance of deep CNNs in terms of accuracy, sensitivity, and specificity in detecting skin diseases from dermoscopic images is significantly high compared to the performance of other techniques. Moreover, the study proposed the incorporation of clinical and genetic data to improve the performance of the proposed method.

Tandon & Soni (2023) proposed a study on the review of different deep learning techniques for the classification of skin diseases. The study mainly concentrated on the application of the CNN technique. The CNN technique is widely popular for the best performance in image classification. The study proposed the application of the CNN technique for the classification of different skin diseases from a dataset of dermoscopic images. The study revealed the best performance of the CNN technique in terms of high accuracy rates. However, the study revealed the presence of challenges in the application of the proposed method due to the complexity of the computational process.

Wang & Liu (2022) presented a comparative analysis of various deep learning architectures in the context of skin cancer detection. The authors used a dataset of dermoscopic images and trained different deep learning models, including CNNs, to classify the images as benign or cancerous. The results of the research indicated that CNN-based models have superior performance compared to classical methods such as SVM and k-NN in terms of high sensitivity and specificity. The authors also emphasized the role of pre-processing techniques in improving the performance of deep learning models. However, the authors also discussed some of the limitations of the research.

Wu & Zhang (2023) proposed a method based on deep learning technology for the detection of skin diseases using dermoscopic images. The authors have used CNNs as a tool for the classification of images and evaluated the performance of various architectures of CNNs in the context of skin disease classification. The results of the research indicated the high accuracy of deep learning models in the classification of skin diseases. However, some of the limitations of the research have also been discussed in the context of the use of CNNs.

The problem associated with limited diseases being covered by existing models was addressed by Rohit et al., (2023), who proposed a weightless model that is able to identify 23 different types of skin diseases. Model development involved creating a machine learning model using a PyTorch backend. Dataset expansion involved training the model on a diverse dataset containing 23 different types of skin diseases. Overcoming the limitation associated with existing models being able to identify only specific types of diseases by expanding its ability to identify 23 different types of skin diseases and ensuring high accuracy in detecting diseases are major challenges associated with this problem. The feasibility of using a machine learning model with a PyTorch backend to identify various types of diseases is shown in this study.

Sharma et al., (2021) proposed a convolutional neural network for identifying five different skin diseases. Although a high-dimensional data set could increase accuracy up to 90%, it only attained 70% accuracy.

In Hegde et al., (2018) research paper, a comparison of different machine learning algorithms was conducted for classifying skin diseases using color features as well as texture features. The red, green, and blue values of an image are converted into grayscale using computer vision algorithms and a neural network. The results from the neural network were found to be the highest compared to other algorithms. The accuracy was 62.9% after training the model using four different techniques. The accuracy of 80.9% was achieved by LDA, while 67.4% accuracy was achieved by NB. 81.61% accuracy was achieved by SVM out of the four models, which was found to be the best compared to other models. The comparison of different models gave a clear idea of which model could be more effective for future research studies. The results were found to be correct according to 21 different dermatologists.

Amina Aboulmira et al., (2024) undertook a systematic review that revealed the most common cancer in the world is skin cancer. It further revealed that the best outcomes are achieved when the patient is detected early. This systematic review provided a comprehensive discussion on the numerous AI techniques employed in the categorization of skin diseases. It further emphasized the effectiveness of the techniques in dealing with different datasets. Originally, 220 publications were retrieved from databases like IEEE Xplore and Scopus. 213 studies were included in the review after evaluating them against predetermined standards like study relevancy, result clarity, and creative AI approaches. Finally, 56 studies were included in the final review after full-text evaluation. Convolutional Neural Networks, Transformer models, hybrid models combining CNN and other models, Generative Adversarial Networks, and ensemble methods were some of the AI models that were applied in the classification of these studies. According to the review, due to the sheer volume and variety of dermoscopic images, the ISIC dataset and its variants are the most frequently applied data source. According to the study, CNN-based models are still the most popular and successful approach in classifying skin diseases, though some hybrid models and even some models based on the Transformer approach have shown promising results in terms of accuracy and specificity. Despite all these advancements, issues like data inconsistency, the need for more varied data, and the inability to interpret AI models still exist.

Brinker et al., (2024) applied deep learning-based CNN in skin cancer classification. A systematic review was conducted, and special emphasis was given to dermatology and CNN. It was concluded that deep learning algorithms are more accurate and can directly analyze raw image data without needing much pre-processing. Hence, they are increasingly being applied instead of traditional machine learning algorithms, according to this systematic review.

Zhang et al., (2023) provided an extensive review on deep learning and machine learning-based image analysis in dermatology. Emphasis was given in the review on the significant advancements in CNN models, including ResNet, AlexNet, VGG, and so on, and how they have improved the diagnostic capabilities of various skin conditions, including both common and uncommon conditions. At the same time, difficulties in handling imbalanced datasets and the limitations in terms of interpretability have also been pointed out.

The study conducted by Wu, et al., (2022) on cutting-edge methods like transfer learning and GANs, and their usage in dermatological applications was examined in a more recent review. The study emphasized that, while these methods show promising ways to circumvent the problems related to sparsely labeled data and increase model generalizability, further evaluation methods and increased datasets are required to achieve these methods' full potential.

The study conducted by Gordon et al., (2024) emphasized how important it is to ensure patient data privacy, transparency, and clinical validation before these models can be extensively utilized in practice. This study provided an avenue for further research, particularly in addressing issues like dataset bias, model interpretability, and the ethics of AI in dermatology. This method enables us to track the development of these methods, particularly emphasizing the increased acceptance and improvement of deep learning methods, particularly CNNs, Transformers, and hybrids.Choy et al. (2023) used Support Vector Machines for skin disease diagnosis. Here, an automated skin disease diagnosis system was developed using SVM for image classification tasks to improve diagnostic accuracy and reduce manual effort in disease identification. This was effective for structured and low dimensional data. Nevertheless, the system struggled with high-dimensional dermoscopic images and suffered non-diverse datasets

Adarsh et al. (2023) proposed a CNN model in predicting skin diseases. The CNN Model was applied in classifying skin diseases. It provided high accuracy and fast results. However, it was not generalized, imbalanced, and had issues related to data privacy and integration.

Ashwini et al. (2023) proposed a system that can quickly and accurately identify skin diseases and suggest appropriate treatments. Machine learning algorithm and deep learning algorithm were applied in classifying diseases and proposing solutions. It improved the speed and accuracy in diagnosing diseases. It lacked image variation and consistency in diverse populations.

Malik et al. (2024) proposed an efficient CNN model in diagnosing skin diseases. It was applied in images taken through dermoscopy. It was compared with traditional models, CNN, and hybrid models in determining the most efficient method in obtaining accurate results. It was efficient in diagnosing skin diseases. It was not clear how the model made decisions, and its practical efficiency in medical scenarios was questionable

III. MATERIALS AND METHODS

3.1 Research Methodology

The research applied a Systems Development Life Cycle (SDLC) methodology. It entailed the use of document review and site visit to systematically extract the following challenges:

i. Small and Unbalanced Datasets: Most existing systems rely on small or uneven datasets that over represent certain diseases, causing bias and poor accuracy.
ii. Lack of Real Clinical Integration: The reviewed ML and DL models for skin disease diagnosis remain at the research level and are not practically implemented in hospitals or clinics.
iii. Poor Generalization Across Populations: Current models perform well only in controlled environments but fail when applied to patients with different skin tones, ages, or imaging conditions.
iv. Lack of Transparency (Black-Box Models): Most AI models do not explain how they make predictions, reducing trust among clinicians.
v. Ethical and Regulatory Issues: Existing systems often neglect ethical concerns such as data privacy, fairness, and medical compliance.

3.2 Design of the Proposed Model

The following were incorporated into the proposed system's design:
The proposed system incorporates Explainable AI (XAI) to ensure the predictions are easily understood by the doctors.

The proposed system will be trained on a wide range of data to improve the generalization of the system. The proposed system creates a large dataset that is diverse and balanced to improve reliability and fairness. Hence, the proposed system is suitable for actual implementation. Different system analysis tool were used to show how the proposed model will behave,

The first is Unified Modeling Tools (UML). The tool was used in the design of the suggested system. It captures the functionality of software and gives overview of the major players in the model (see Figure 3).

An activity diagram was also used to show how the proposed model operates (Figure 4). The Class diagram was used to display the suggested model's structure (Figure 5), and the sequence diagram showed how two more of its components interacts (Figure6). The model's working process is demonstrated using the unified modeling language diagram, activity diagram, and high-level architecture (Figure 7).

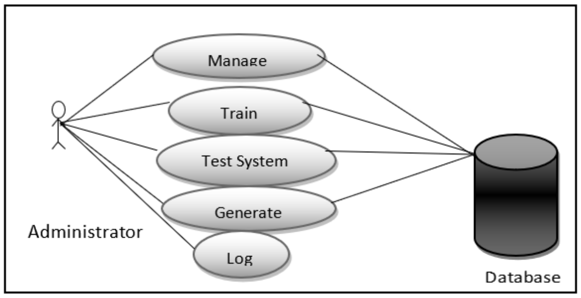

Figure 3: Use Case Diagram of the proposed System

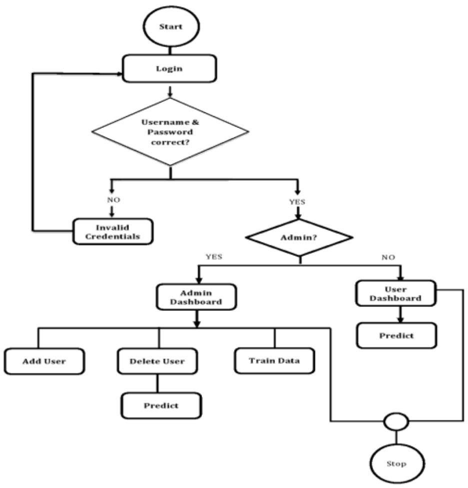

Figure 4: Activity Diagram of the CNN-Rule based model for skin disease determination

The Workflow Activity Diagram for the Skin Disease determination model in Figure 4 is as follows:

Start:
The system begins when a user or admin opens the application.

Login:

- The user enters a username and password.
- The system validates the credentials.

Credential Verification:

- Invalid Credentials:
  If incorrect, the system displays an error message and returns to the login screen.
- Valid Credentials:
  The system checks whether the user is an Admin or a Normal User.

Access Control:

Admin:
Redirected to the Admin Dashboard, where they can:

- Add Users
- Delete Users
- Train Data for prediction
- Predict skin diseases from images
- Stop or log out

Normal User:
Redirected directly to the User Dashboard, where they can:
Predict skin diseases from uploaded images
Stop or log out
Prediction Process:

- The user uploads a skin image, and the trained model predicts the type of skin disease.
- End/Stop:
  The process stops after actions are completed.

The diagram in Figure 5 represents the class diagram of the CNN-Rule based model for skin disease determination. It has the following classes: Image Dataset, CNN Model, and Skin Disease Prediction. Image Dataset has attributes for images and labels, while CNN Model has methods for training, prediction, and evaluation. Similarly, the Skin Disease Prediction (CNN-Rule based) class is for prediction.

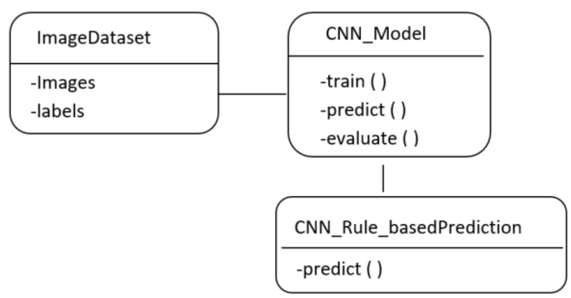

Figure 5: Class Diagram of the proposed System

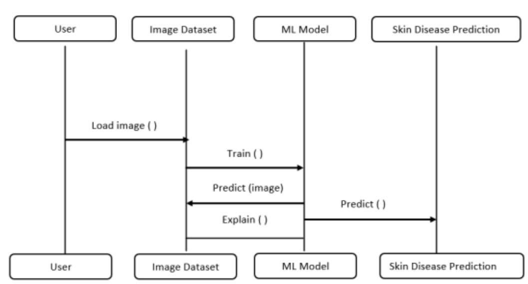

Figure 6: Sequence Diagram of the System

Components of the Proposed System architecture

Unstructured Image Data: Unprocessed image data in a raw format like JPEG, PNG, etc.

Structured Image Data/Info: Image data that is already processed and available in a format that is easily amenable to processing (for example, pixels are already labeled).

Pre-trained ML Model (CNN): A pre-trained machine learning model that is already trained on a large dataset, usually a Convolutional Neural Network (CNN), which is highly effective for image processing tasks like image classification.

Database Model: A structured way of representing the data in a database that helps in organizing the image data for efficient use in training the ML model. Neural Network: A neural network is a network of interconnected nodes called neurons. These neural networks are capable of learning complex patterns from the data. These networks are often employed in image processing for tasks like image classification.

Rule-based Classifier: This is a classification system that uses a set of predefined rules to perform classification on data. In this case, it could be used to classify skin lesions based on image features and other attributes.

Image Processing: This is a technique used to improve or change images to enable further analysis. This is done by removing image noises or improving contrast to enable separation of objects within an image.

Trained ML: This is a machine learning model that has been trained to enable predictions or classification on data.

Decision Support: This is a system used to aid in decision-making processes. This is commonly used in clinical situations to aid in decision-making. It uses Emgu.CV recognition filter and emotional/symptoms filter

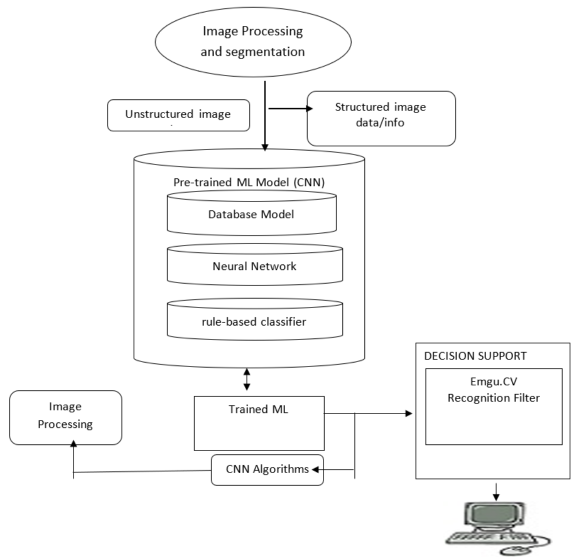

Figure 7: High Level Architecture of Proposed System Architecture

The diagram shows how the skin disease prediction system works. The system begins with unstructured image data, which includes raw skin disease images. The raw image data is processed using image processing techniques to clean the data and make it structured.

The main part of the system is the CNN model, which has three parts:

- Database Model – Stores and organizes the images.
- Neural Network – Learns patterns from the images.
- Rule-Based Classifier – Uses rules to help classify the skin disease.

Table 2: Comparison table

Author / Year	Model Used	Dataset Used	Advantages	Limitations
Proposed Model (2025)	CNN + Rule-Based Hybrid	General multi-class skin images	Strong generalization; Interpretable	The system will still need the help of a human to upload skin infection/disease image to process for it to work.
Adarsh et al. (2023)	CNN-only (Deep Learning)	HAM10000 dermoscopic dataset	Strong feature extraction; Good on dermoscopic images	No rule layer; Misclassification in borderline cases
Khan et al. (2019)	SVM + Handcrafted Features	Small custom dataset	Fast training; Low computation	Low accuracy (78%); Weak feature representation
Rangarajan et al. (2020)	Traditional ML (KNN, DT, RF)	Limited dermatology dataset	Simple; Interpretable	Low accuracy (74%); Not suitable for complex lesions
Shabbir et al. (2019)	Handcrafted + Classical Classifiers	Mixed-source small dataset	Simple to implement	Low accuracy (70–75%); Not robust
Choy (2023)	Traditional method (SVM)	General skin-disease dataset	Low computation; Interpretable	Low accuracy; Rules ineffective

IV. CONCLUSION

The paper is relevant to the area of investigation, and it shows how machine learning can be applied in predicting skin diseases, and how CNN-Rule-based classifiers can be applied in the medical domain. The studies show that they are related to the role that machine learning has in improving the accuracy of the prediction and minimizing human error, and they provide assistance in making an informed decision for medical professionals. Moreover, it provides a stage for future research in healthcare AI, particularly in dermatology, since it emphasizes the need for efficient solutions

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