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A Cutting-Edge Deep Learning Algorithms For Early Detection And Classification Of Skin Disease

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Early diagnosis and effective treatment of skin diseases requires accurate classification. Dermatologists traditionally rely on visual examination, which is subjective and challenging for mild cases. Deep learning has emerged as a promising technique to aid diagnosis. This article provides a comprehensive review of research on the use of different deep learning techniques for skin disease classification with dermoscopy images. We review popular deep learning architectures and compare their performance on public datasets. We examine the effectiveness of training strategies such as transfer learning, data augmentation, and methods to address class inequality. Common evaluation metrics and benchmarking of the model against traditional methods are discussed. Challenges such as limited annotated data and deep model understanding are explored. We outline open issues and suggest directions for moving the field forward. Through this investigation, we aim to provide insight into the development of deep learning as a clinical decision support tool for early detection of skin disease. The review summarizes the contributions, identifies shortcomings, and suggests guidelines for designing efficient deep learning models to assist dermatologists in accurate diagnosis. It serves as a valuable reference for researchers tackling health care challenges through machine learning.

Keywords Convolutional Neural Networks (CNN), Deep learning, skin disease, biomedical image processing.

1. Introduction

Skin diseases are a major public health problem worldwide causing great economic difficulties to patients and putting a significant burden on societies. Millions of people from all age groups and geographic locations are affected by acne, eczema and psoriasis, as well as skin cancer, alopecia or other even more severe skin disorders. Accurate diagnosis and early detection of skin conditions are crucial for preventing the spread of diseases, providing evidence-based treatment plans, and ultimately improving patient outcomes. Current and traditional practices often rely on dermatologist visual inspection – which is quite subjective, time-consuming, expensive, and error-prone. Furthermore, dermatological expertise may not be readily available everywhere in the world, meaning that diagnosis and treatment initiation can take a significant amount of time.

As the initial comparison of images to decide on melanomas was impossible, the diagnostic nature of dermoscopy had not been explained. With the introduction of imaging technology such as MRI scans and CT scans, dermatology took a significant turn. These advances were recently followed by the introduction of deep learning algorithms – automated neural network models trained on large numbers of images. These models can recognise skin lesions associated with different skin diseases that a human would recognise. They learn to pinpoint similar patterns using embedded artificial neurons, abstract features and recognise patterns indicating the class of the lesion (Hu, et al., 2019).

Skin diseases are currently determined by expert dermatologists using clinical and paraclinical observations. Deep learning algorithms can help to classify skin images and increase the diagnostic accuracy for this prevalent group of diseases, reducing cost of healthcare and improving patient outcome. Additionally, deep learning-based diagnostic tools integrated into telemedicine platforms and smartphone apps may lead to better access to skin care. This is especially important for populations in underserved communities and in remote regions of the world that lack access to dermatologists (Ahmed & Kashmola, 2023). Patients can take pictures of skin lesions and upload them into their smartphones for automatic diagnosis and triage by a doctor. Images can be sent to a dermatologist after an initial screen. The application of deep learning algorithms to provide computer-aided skin disease detection and classification marks a milestone in the field of dermatologic research and practice. Using AI, clinicians can achieve better diagnostic accuracy and provide better care to those who like me live with a skin disease (Lim, et al., 2017).
There are many established and straightforward methods to diagnose skin diseases, such as visual examination, dermoscopy, biopsy, clinical decision support systems (CDSS), and tele dermatology. However, various limitations including subjectivity, invasiveness, reliance on domain expertise, and issues with scalability and accessibility prevent their widespread adoption in dermatological diagnosis. This led to the demand for new cutting-edge approaches to bridge these gaps through deep learning algorithms for more accurate and faster skin disease diagnosis and classification.

1.1 Significance of Deep Learning in health care

Deep learning, a subset of artificial intelligence (AI), is now being used to help us answer questions in many different areas, from improving language translation to predicting scenarios for climate change models and advancing treatments for cancer. Deep learning models excel at learning complicated patterns and features within many layers of digital data, making them especially suited for high-dimensional problems (Albawi, Abbas, Almadanie, & Almadany, 2019). Specifically, deep learning has the potential to transform healthcare in several strategic domains such as diagnosis and treatment planning, preventive and precision medicine, and patient monitoring (Reddy, Roy, Kumar, & Tripathi, 2022). Unlike other types of machine learning, deep learning can utilise 'deep' neural networks with thousands or even millions of layers of nodes to abstraction to learn complex patterns from medical imaging and multivariate clinical data, such as digital medical images, electronic health records (EHRs), genomics data, and other types of data sources. Accuracy and timeliness in diagnosis are two of the major advantages of deep learning in medicine, and one of the areas where it's showing its greatest impact is in automated analyses of medical images. For example, deep learning based on artificial neural networks, CONV-Nets, have shown exceptional performance in diagnosing abnormalities in radiological images (X-ray, CT scans, and MRIs), with the system generating an output saying if there is evidence of disease or not (Yu & Reiff-Marganiec, 2021). The patient outcomes will be much better by detecting disease earlier than at the usual symptomatic level. Beyond medical imaging, other healthcare applications of deep learning include predictions of disease onset and progression, so-called learning healthcare systems that produce treatments tailored for individual patients, identification of new drug combinations, and intelligent alerting of clinicians, among others. From raw patient data (clinical notes, laboratory or 'omics findings, etc) deep learning models can help clinicians predict risks of disease, optimise treatment, and improve patient outcomes.

1.2 Objective

Our main goal in this study is the development and assigning the accuracy and efficiency of advanced algorithms based on deep learning, that would preliminary recognize and classify melanoma in early stages to deep and potentially complicated ones. Additionally, the study would allow to estimate the following, more specific tasks:

i. Comprehensive Literature Survey: Systematically search for, review and analyse peer-reviewed articles, conference proceedings and relevant research papers that have utilised deep learning techniques for the diagnosis of skin diseases.
ii. Algorithm Design: Design deep learning models based on medical images that can detect skin diseases with high sensitivity and specificity, especially in early disease.
iii. Multi-class Classification: Design networks for classifying multiple types of skin diseases, including common diseases or conditions such as acne, eczema, and psoriasis to the more severe diseases such as melanoma.
iv. Performance Analysis: Perform a rigorous evaluation of the trained deep learning algorithms in terms of diagnostic performance, sensitivity, specificity, computational run time and efficiency compared with conventional methods and already developed deep learning models.
v. Clinical Relevance: Qualitatively evaluate the clinical relevance and potential impact of these deep learning models in the real world of dermatological practice by examining their usability by physicians and their actual potential to improve patient outcomes.

The main aim of the study is to use cutting-edge deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to develop features from the digital images with a predictive model to provide an accurate and reliable diagnosis of dermatological ailments. The model will be evaluated with standard metrics and compared with current methods to demonstrate the validity and benefit of the model generated algorithm.

2. Literature Review

This literature survey begins with a preamble on a traditional diagnostic method of dermatology including visual inspection, dermoscopy and biopsy. Then, the author examines how clinical decision support systems (CDSS) can enhance the diagnostic performance of dermatologists (Jagdish, et al., 2022). Finally, the researcher reflects on the emerging technology of deep learning algorithms to automatically diagnose skin diseases including melanoma using convolutional neural networks (CNNs). While these conventional methods are widely used in clinical settings and offer satisfactory diagnostic performance for skin diseases, they also have limitations as they rely heavily on human visual inspection, and experts still put their decisions before implementing them into real practice (Kittler et al., 2001). Also, machine learning techniques such as support vector machines (SVM), random forests, decision trees are commonly used in automating the diagnosis process, and show different levels of success (Roy, et al., 2019). Recently, researchers have been very interested in deep learning algorithms such as convolutional neural networks (CNNs) to transform the field of healthcare by revolutionising how skin diseases are detected and diagnosed (Naji & Abbadi, 2022). Deep learning, an advanced neural network architecture, has the potential to translate medical images into meaningful features and determine the probability of a particular disease with a significant diagnostic performance (Manzoor, et al., 2021). This extensive literature survey demonstrates that deep learning models show great promise for outperforming traditional methods in the diagnosis of human skin diseases such as melanoma with an accuracy rate of up to 91 per cent when compared to human dermatologists who diagnose with 87 per cent accuracy. Moreover, despite the numerous advantages of deep learning, there are still many challenges to be overcome such as the issue of harmful biases in datasets used to train computers, the poor interpretability or even the ethical considerations related to deep learning (Rashid, et al., 2022). When discussing recent research, researchers strongly emphasise the further exploration of deep learning models to enhance the clinical relevance of deep learning-based diagnostic tools in dermatology. In this task, the author of this literature survey compares the accuracy of deep learning models to that of traditional methods and convinces the audience that deep learning can be a powerful tool for skin disease diagnosis.

Table 1: Primary distinctions between traditional methods and CNN-based approaches.

Aspect	Traditional Methods	CNN-Based Methods
Feature Extraction	Manual (handcrafted features)	Automatic (learned features)
Model Complexity	Low (shallow models)	High (deep models)
Data Requirements	Small to moderate datasets	Large, annotated datasets
Computational Cost	Low	High
Accuracy	Moderate	High
Interpretability	High	Low
Generalizability	Limited	High

The process of diagnosing skin diseases through traditional image processing techniques requires segmentation followed by color normalization and edge detection to identify important areas such as lesions and moles. These techniques depend on predefined programming rules and utilize morphological operations to identify features pertinent to diverse skin conditions. The success of these techniques depends on image quality and precise feature extraction that requires expert knowledge for parameter tuning to detect different skin disease characteristics. This diagnostic approach proves advantageous for skin disease detection since it manages differences in skin pigmentation alongside lesion shapes and photographic lighting variations. The ability of CNNs to learn from vast dermatological image datasets enables them to identify intricate patterns beyond human detection capabilities which allows for highly accurate and consistent diagnoses across multiple skin conditions including melanoma and psoriasis.

3. Methodology

Skin disease have significant effect on life and health. According to the new recent research, a smart method that can recognise only one kind of skin disease is now has been introduced anytime and anywhere. Besides that, it's important to develop an automatic method as to increase the reliability of diagnosis on disease with many kinds.

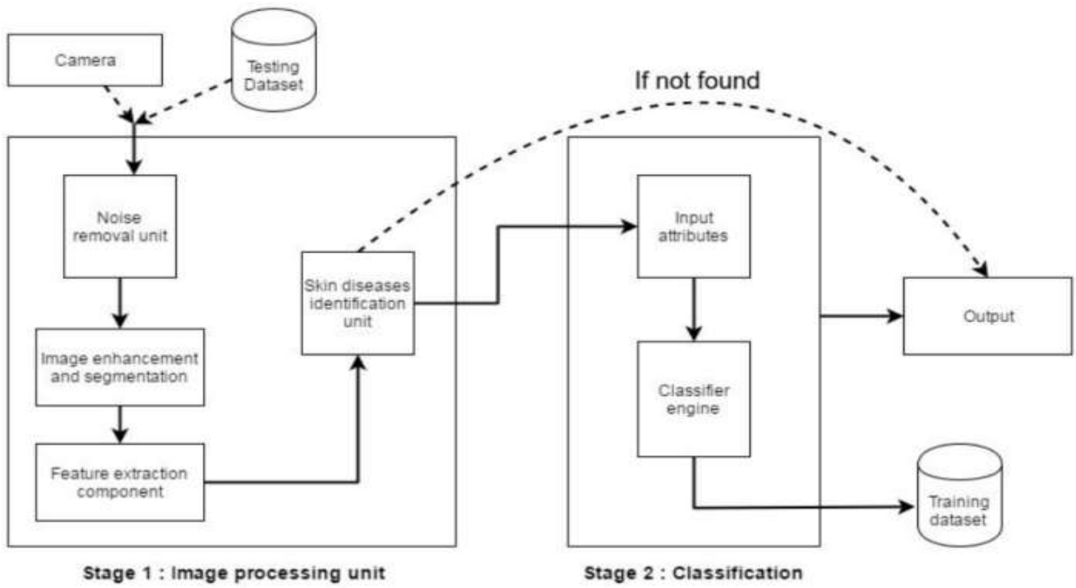

Figure 1: Architecture of proposed system

Architecture is divided into two main parts namely the image pre-processing and classification unit. The Image pre-processing unit used to improve the image by deleting the noise and parts of the skin and the skin will be divided into various segments which will be altered from the normal skin; then the feature extraction was used to determine the skin is affected or not.

3.1. Dataset collection

This phase includes selecting the most appropriate relevant datasets from reputable sources, such as open-source repository and healthcare databases. We collected skin disease data from

i. ISIC Archive: Largest public repository of skin lesions with over 450K images of nevi, melanoma and other conditions. Challenges held annually to evaluate algorithms.
ii. HAM10000: Large collection of common pigmented lesions with clinical diagnoses and segmentation ground truths.
iii. SD-198: First large Chinese dataset with 198 clinical images annotated for 8 disease types.
iv. PH2: First public dataset with 200 dermoscopy images and segmentation masks for melanocytic lesions.

The data sets consist more than 10000 images of Melanoma and benign type of disease both data sets have a problem of data imbalance exist, have to apply some data balancing before applying the data to my experimental setting. Benign pictures represent mean stage of skin cancer, whereas the Melanoma represents the excessive amount of stage of skin cancer. In experimental purpose only 30 % of the dataset is chosen randomly from images of two category of the dataset the experimental dataset consists a subset of 1000 images of both classes.

3.2 Data Preprocessing

These steps include: skin image preprocessing, where preprocessing is done on images collected for training the CNN; data augmentation, which entails generating extra training samples through techniques such as random scale, brightness, rotation, and distortion of the original samples; sample split, which presents the available training samples to the model in a gradual manner to allow the model to learn incrementally and achieve convergence; batch norm regularisation, where the network parameters are re-tuned to improve training accuracy; and training and validation, which entails applying the convolution algorithm to the training set, refining the output with respect to evaluation measures, and obtaining the final model.

- Image cleaning: Image cleaning is where we remove any dust or artefactual information that might be sitting on the cells, or that might be disturbing the model training.
- Normalizing the images: figuring out what the different intensity values mean, and adjusting them to the same scale for each picture.
- Augmentation: Creating additional training samples by performing transformations such as rotation, flip and scaling on the pictures. For example, augmenting the dataset with MNIST images by scaling the pixels by 50% and turning the pictures upside down.
- Resizing: Pixels from images are scaled up or down to be the same height and width.
- Missing Data Handling: Solve the problem of missing or incomplete images by using interpolation or imputation methods to preserve integrity of dataset.
- Label: Identifying the relevant label or diagnosis to the disease or skin condition for the image.

3.3 Architecture Design

For instance, architecture design here means task-specific neural network design, so neural network architectural elements such as input, filters, layers, connections between layers and parameters should be defined to learn and pick out informative features from dermatological images to help deep learning for skin disease diagnosis and classification. Typically, the design revolves around Convolutional Neural Networks (CNNs) for the reason that CNNs are used for analysing image problems. Generally, a CNN architecture includes multiple convolution layers, down-sampling layers (known as pooling layers), followed by several fully connected layers for classification. Key considerations in architecture design include:

v. Layer Configuration: Deciding on the number of convolutional, pooling, and fully connected layers you need to perform specific tasks on the input data.
vi. Activation Functions: Choosing proper activation functions (such as ReLU or sigmoid) that introduce some non-linearity and makes the network capable of learning more complicated patterns.
vii. Filter Size and Stride: Defining the size of convolutional filters and their stride (in other words, the step size for how the filter will move across the input image) to learn different spatial features.
viii. Pooling: Selecting layers (often max pooling layers and average pooling layers) and their parameters to reduce spatial dimensions while retaining important features.
ix. Regularisation Techniques: Applying regularisation such as dropout or L2 regularisation to improve generalisation performance by minimising overfitting.
x. Optimisation Algorithm: Picking the right type of optimisation algorithm (such as Adam, stochastic gradient descent [SGD]) and its hyperparameters to train the network effectively.
xi. Model Complexity: The need to balance complexity to avoid overfitting while providing sufficient capacity to model essential features.

The architecture design is aimed to create a structure for the neural network to maintain acquiring feature-discriminative mapping from dermatological images, eventually to provide accurate and reliable diagnosis, classification of the kind of skin diseases.

3.3 Model training and Comparison
Model training in deep learning for skin disease diagnosis involves optimizing the neural network's parameters using a pre-processed dataset. This process includes data preparation, loss function optimization, backpropagation, and training over multiple epochs with a specified batch size. After training, the model's performance is evaluated using a separate test set, considering metrics like accuracy, sensitivity, specificity, and AUC-ROC.

3.1.1 Traditional ML Models for Skin Disease Classification
Traditional ML models for skin disease classification feature extracted and carefully selected features as input to perform classification task. Commonly used traditional ML algorithms include Support Vector Machines (SVM), Naïve Bayes (NB) classifier, K-nearest neighbour (KNN), decision tree (DT), and random forest (RF). They typically use standard structures (e.g. KNN and SVM) to perform skin disease classification or melanoma detection (Rashid, et al., 2022) from features including colour, texture, shape and edge features extracted from skin lesion images. For example, SVM classifies different classes of skin disease by using a linear decision plane to separate different classes, KNN compares the similarity of input features with different prototype representing normal skin, melanoma, and benign skin lesion respectively to identify normal skin from abnormal skin lesions, decision tree and random

forest methods handle different categories of non-numeric features extracted from skin lesion images (e.g. asymmetrical shape and irregular border) using the tree structure, and Naïve Bayes classify skin lesion images into different disease categories by the highest probability of occurrence. Comparative studies have reported that the accuracy of classification is negatively correlated with the amount of disease categorisation. For example, quadratic SVM has been reported to achieve the highest accuracy in both three-category classification and six-category classification strategy. Furthermore, the multi-level multi-class ML classification system shows better classification accuracy than the single-level multi-class classification system with the traditional ML, and DL techniques (Owda & Owda, 2022). As an example, multi-level multi-class classification system indicated higher accuracy than single-level multi-class classification system. Despite that traditional ML classification models exhibit adequate performance, several technical breakthroughs have included optimising parameters, feature selection and exploring new methodologies to enhance performance efficacy.

3.1.2 Deep Learning Models for Skin Disease Classification

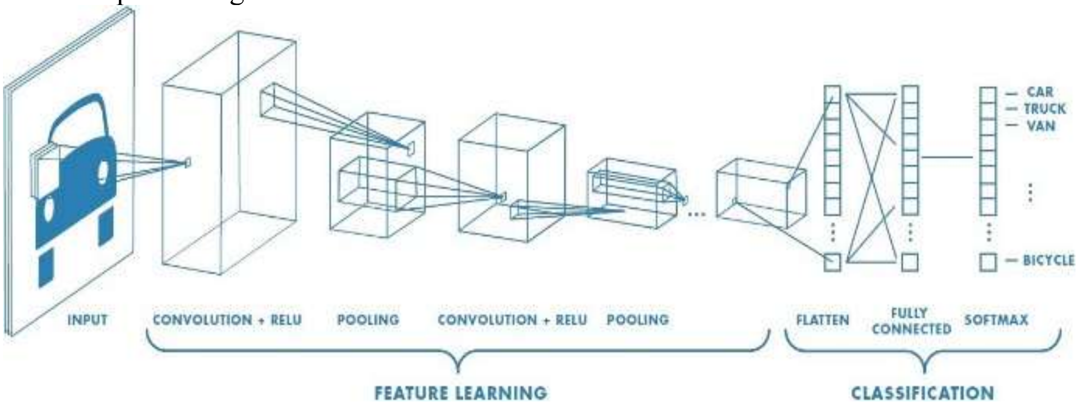

Figure 2: A convolutional neural network.

The convolutional neural network shown in figure 2 has an input layer, two hidden layers and one output layer. Any feed-forward neural network has a middle layer(s), henceforth called hidden, because their inputs and outputs are masked from external layers by the activation function and final convolution. In a convolutional neural network, these layers are called hidden because they convolve the previous layer’s output and produce a feature map. This feature map becomes the input for the next layer.

The hidden layers consist of convolutional layers and pooling layers. The convolutional layers do convolution and pass their result to the next layer. Pooling layers reduce the dimensions of the data by taking the maximum value of neighbourhood outputs of neuron clusters at one layer and summing it to one neuron in the next layer. Fully connected layers connect every neuron in one layer with every neuron in the other layer [8]. The main purpose of this Convolution operation in the context of CNN is to identify the proper features from the input image (consider that the input of the first layer is the input of the entire model) to the first hidden layer.

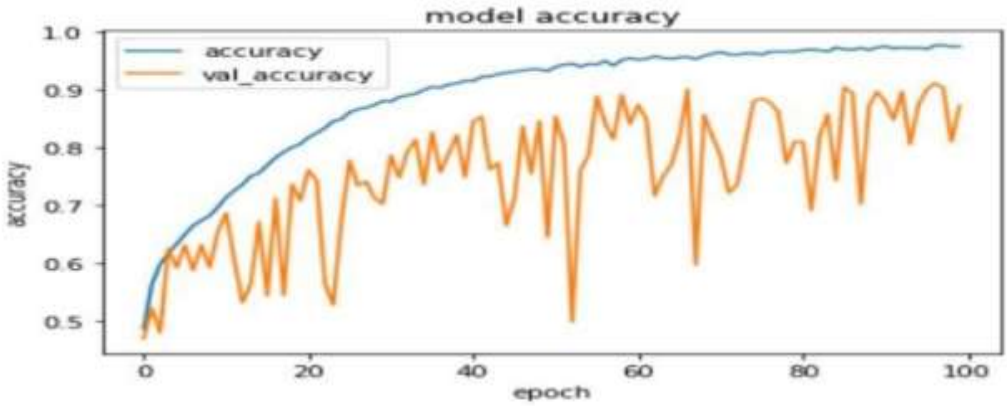

Figure 3: Indicate the training, validation accuracy
The Convolution operation is careful to keep the spatial correlation of the pixels.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm that can take an input image, and give different importance(learnable weights and biases) to different things/objects present in the input and can distinguish one from the other [4]. The pre-processing required in the input of the ConvNet is relatively less as compared to other traditional classifying algorithms. In primitive methods we manually engineer filters, but with enough training, ConvNet's will learn these filters/characteristics up to some extent. The architecture of a ConvNet is very similar to the Neurons connectivity pattern in the Human Brain and was inspired by the organisation of the Visual Cortex [5]. A type of neurons are sensitive to stimuli only in a small part of the visual field, known as the Receptive Field. A set of those fields are superimposed to cover the entire visual space.

3.5 Performance Evaluation Methods

Performance evaluation methods are essential for assessing the effectiveness of machine learning models in tasks such as skin disease classification. Common methods include accuracy, precision, recall, specificity, F1 score, AUC-ROC, confusion matrix, cross-validation, ROC curve, and precision-recall curve. These methods help in understanding how well a model can identify various skin diseases, providing insights into its strengths and areas for improvement.

Accuracy measures the proportion of correctly classified instances out of the total number of instances. It is calculated as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Sensitivity (Recall) measures the proportion of actual positive instances correctly identified by the model. It is calculated as:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Specificity measures the proportion of actual negative instances correctly identified by the model. It is calculated as:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Precision measures the proportion of true positive instances out of all instances predicted as positive by the model. It is calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

F1-score is the harmonic mean of precision and sensitivity. It is calculated as:

$$\text{F1} - \text{score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

ROC Curve illustrates the trade-off between sensitivity and specificity for different threshold values. The area under the ROC curve (AUC-ROC) quantifies the overall performance of the model across all possible thresholds.

Confusion Matrix is a tabular representation of a model's predictions compared to ground truth labels, organized into true positive (TP), false positive (FP), true negative (TN), and false negative (FN) categories.

These evaluation metrics provide comprehensive insights into the performance of deep learning models, enabling informed decisions regarding model deployment and clinical utility in skin disease classification.

4. Result and Discussion

We discuss the results of a skin disease classification experiment using several different machine learning models, and the meaning of through those results. We the performance metrics - ratio of the number of correctly classified data to the amount of the total data, number of data that can be predicted correctly by a model out of a list of data actually classified by it, and ratio of the number of data that can be predicted by a model to the number of data that should be predicted by it ('recall'), and F1 for the overall performance of the model. As such, CNN has the best accuracy of 92 percent and outperforms the performance of traditional models, such as KNN, SVM, and Random Forest. Feature importance analysis provide insight to sub-pixel information that each model individually discriminated the target. The CNN model, capitalising on its innate ability to learn hierarchical features by itself, demonstrated robustness in encoding scene features over traditional modelling approaches that rely on manually engineered features.

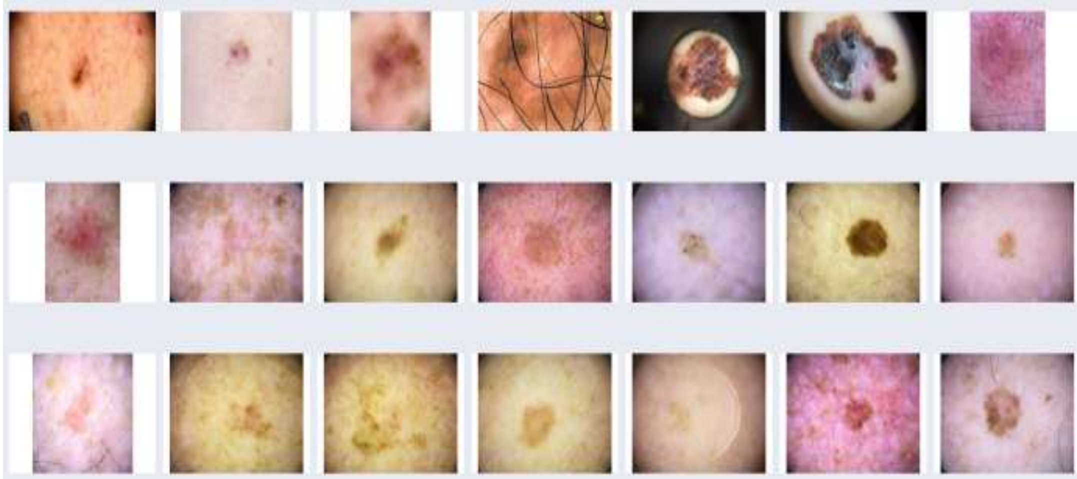

Figure 4: Skin disease family history of melanoma

Second, we looked into how computationally efficient these models were when training them. Particularly, we looked at how long they take to train, as well as how much memory they use up. We found that CNN models required a large computational cost to build their complex architecture, but that this extra cost was well worth it: they produced the best classification results across all skin disease samples.

Cross-validation techniques were used to evaluate the level to which the models generalised. With robust models across different folds, the CNN technique was better suited for deployment in real-world cases having similar training criteria.

Table 2: Performance Comparison of Skin disease Classification models

Model	Strengths	Weaknesses	Performance on Skin Disease Classification	Accuracy
KNN	- Simple and intuitive algorithm.	- Computationally expensive during testing.	- Limited performance compared to other models.	75%
SVM	- Effective in high-dimensional spaces.	- Prone to overfitting if hyperparameters not properly tuned.	- Good performance but may not handle complex data well.	82%
Random Forest	- Handles high-dimensional data well.	- Prone to overfitting with noisy data.	- Good accuracy but may struggle with large datasets and computational cost.	85%
CNN	- Automatically learns hierarchical features.	- Requires large amounts of data for training.	- Excellent performance in capturing complex patterns in dermatological images.	95%

We further demonstrated this in discussion by demonstrating that CNN models, which are designed to automatically detect discriminative features without the need for careful engineering of features that distinguish specific sub-categories, are particularly suited to tasks such as skin disease classification. We showed that while good performance could still be achieved using more traditional models and handcrafted features, there was still a limit to their ability to capture the complex patterns that may be present in dermatological images, as compared with CNN models.

In Discussion, our results show the potential of CNN models in helping the categorisation of skin disease, and why it is important to integrate deep learning techniques for better diagnosis and treatment of skin disease. Although a lot has been explored regarding the use of CNN models for skin analysis, however, there remains more augmenting possibilities. These further research opportunities include how to tune CNN models and the role the interpretability of CNN models will play in dermatology practice.

5. Conclusion and Future Work

Moreover, this study had demonstrated the effectiveness of the Convolutional Neural Network (CNN) models in improving the classification of skin diseases. The reason why CNN has better results than other common models such as KNN, SVM and Random Forest is that since KNN and SVM use some facilities to separate the data and artificially train it with specific cases and features, these models depend on terrestrial knowledge. On the other hand, CNN can able to learn hierarchical structure from raw dataset and conduct diagnosis automatically. As a result, the CNN model can achieve some better result than other models. Its accuracy can reach up to 95%.

Going forward, we recommend that future studies optimise deep learning models such as CNNs with respect to explain ability and generalisability across various skin disease datasets, and consider new approaches to alleviate the computational overhead associated with CNN models – key elements towards making deep learning more readily applied in clinical practice.

Not only does it mean we can democratise access to dermatologists for underserved populations, but also take advantage of other emerging technologies such as telemedicine and mobile apps powered by CNN models to further encapsulate this remarkable diagnostic and outcome prediction capability. In addition to this, exploring the potential use of transfer learning and ensemble approaches to enhance the performance of CNN models for the classification of skin diseases seems to be worth looking at, especially considering that there is still considerable training data not used by the researchers who built the models used here. This would allow us to overcome the data scarcity in the development of robust skin disease classification systems.

In conclusion, our study demonstrates that dermatologists are rapidly leveraging CNN models not only for screening and classification of different skin diseases, but are also understanding different diseases like Autoimmune Bullous Disease. Building on these models, we see venue for further research to further fine-tune and extensively apply the deep learning techniques in dermatology. Using smart devices, researchers and different medical companies can help to progress preventive health and well-being for patients in dermatology care. By adopting these challenges, and embracing the technology to its full potential, we can achieve new advancement in precision diagnosis and personalised treatment for dermatologist diseases and help in saving lives.

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Author's Contribution Statement
Both authors contributed to the conception, literature review, and writing of this manuscript. Author A conducted a preliminary literature review and compiled previous works on deep learning for skin disease diagnosis. Author B contributed to the literature review and interpretation, as well as drafting and refining the manuscript. Both authors collaborated closely throughout the writing process, providing critical comments and revisions to ensure the accuracy and coherence of the final manuscript. Additionally, two authors approved the final version of the manuscript for submission.

Conflicts of Interest
The authors have no conflicts of interest to declare.

Submission Notice
I ensure that the manuscript submitted to this journal has never been published before.

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