Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/1hthv124

SKIN DISEASE CLASSIFICATION USING DEEP LEARNING

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Abstract
Skin diseases are a major public health problem around the world. Millions upon millions of people suffer from them. Accurate and timely diagnosis is key to effective treatment of skin conditions. In this paper, we introduce a Deep Neural Networks (DNN) based Skin Disease Classification System. This proposed system employs machine learning to automatically categorize skin diseases from dermatological images. Using a deep learning model trained on an extensive collection of dermatological images is the focus of our study. The scope of the data set is broad and covers a variety of skin conditions, which allows the model to recognize complex patterns and characteristics related to different illnesses. We look at the possibility of using Convolution Neural Networks (CNNs) as a more specialized form of DNN to infer spatial hierarchies in skin images, so that we can bring out this fine distinction between diseases. In the training process, it is necessary to fine tune DNN so that its classification accuracy for skin diseases can reach a high level. Accuracy, precision, recall and F1 score are used to assess the achievements of our system. The results show that the DNN model is an effective tool for differentiating between skin conditions. A useful tool for dermatologists and healthcare professionals to augment their diagnostic capabilities The proposed Skin Disease Classification System therefore represents an advance in the field. Such an automated system makes rapid and consistent diagnosis possible, which should help cut the time to take treatment decision. In addition, the application of deep learning methods makes for scalability and flexibility. The model can automatically train itself as it is being exposed to further data in order to maintain its present level of accuracy or increase that level still more.

Key Words: Skin Disease Classification, Deep Neural Net- works, Medical Image Analysis, Disease Recognition, Medical Image Processing, Pattern Recognition.

Introduction

Lumped together, skin diseases cover a wide range of dermatological problems. They represent one big problem in the healthcare field that continues to expand year by year. Accurately diagnosing skin diseases is very important, but because the number and varieties of skin lesions are numerous, this can be a huge problem. Conventional methodology relies heavily on dermatologists' skills, but it suffers from inter- observer variability and is limited by the lack of experts, particularly in remote areas(Kassem et al, 2012).

Deep Learning, a recent advance in artificial intelligence technology offers new ways to address these challenges. Deep Neural Networks (DNNs), which can learn hierarchical representations, are currently making waves in the application of medical image analysis and dermatology. This paper is about the use of multiple DNNs for skin disease classification. With their advantages in feature extraction and pattern recognition, it may change how we diagnose and treat diseases of the skin. The purpose of our research is to improve the accuracy and accessibility with which skin disease identification can be accomplished today (Sikkanda et al, 2012).

The aim is a fully automated system that can identify different skin disorders with high accuracy, to assist dermatologists and increase the efficiency of diagnosis. Particularly, we look at the effectiveness of different DNN structures for distinguishing details not picked up on by most experienced clinicians. Recent breakthroughs in artificial intelligence, especially Deep Neural Networks (DNN), offer a potential pathway to solve these problems. Learning hierarchical representations, DNNs are revolutionizing medical image analysis and der- matology. This paper explores the use of multiple DNNs for skin disease classification. They are already renowned for their capability to extract features and to recognize patterns, being capable perhaps of changing how we diagnose and treat skin diseases completely. Our research is aimed at boosting the accuracy and conve- nience of skin disease identification. We see the future devel- opment of a completely automated system that can diagnose with high accuracy all varieties of skin disorders (Manne et al, 2020).

The goal of such a system is to help dermatologists in their diagnostic processes, thereby increasing the efficiency with which skin disease can be diagnosed. More precisely, we are concerned with how different DNN architectures compare in terms of their ability to detect details that even the most seasoned clinicians might miss. Keeping pace with the burgeoning field of computational dermatology, we test our work against state-of-the art DNN models. The performance of each model can be measured by its accuracy in classifying different kinds of skin diseases. This approach involves using a large dataset of many publicly available datasets to make sure our models are robust and generalization across the whole spectrum of skin disorders among all patients (Yacouby & Axman, 2020). State-of-the art DNN models are implemented and com- pared, continuing the trend with other work in computational dermatology. The efficacy of each model is measured by its ability to accurately classify different types of skin disease (Juba & Le, 2019).

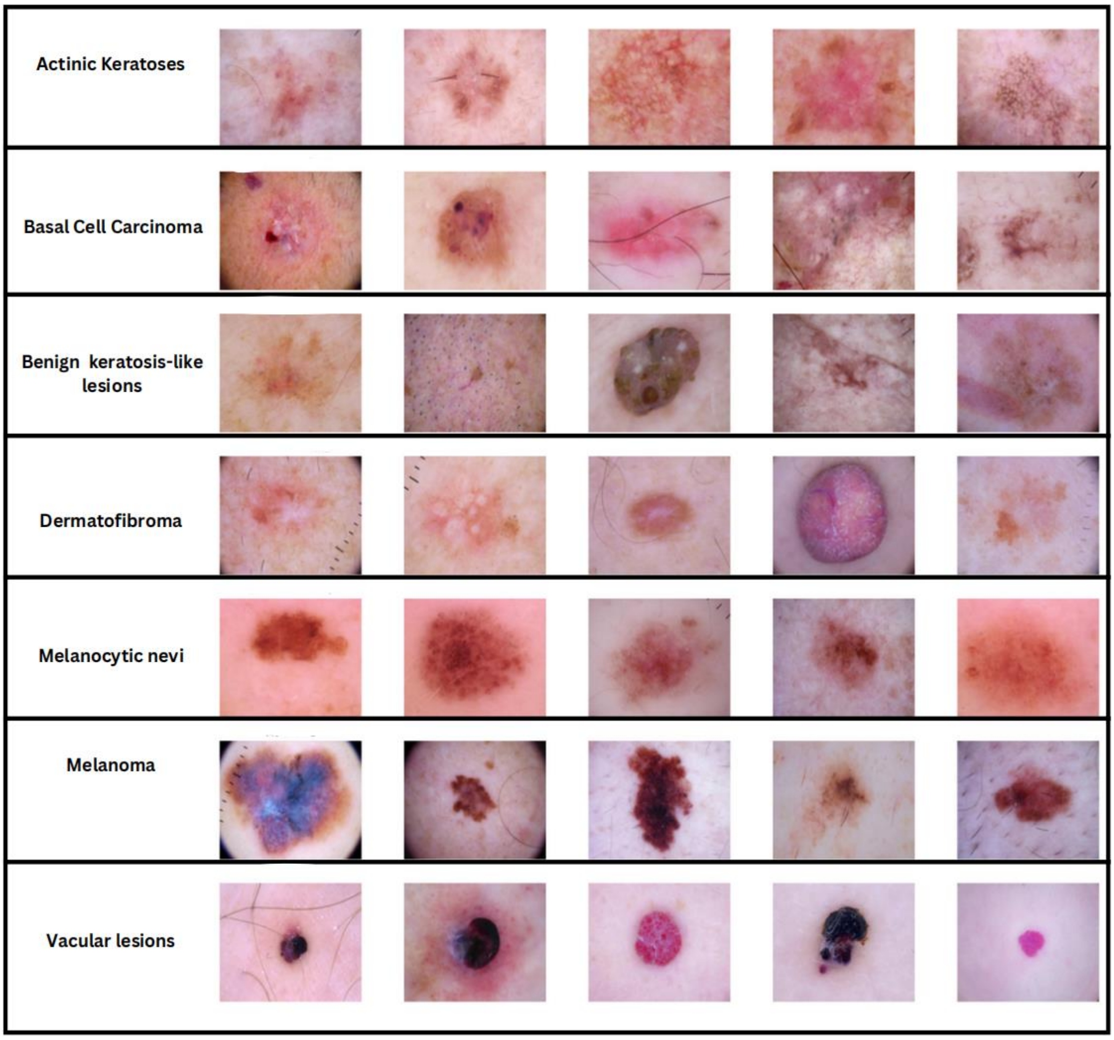


Fig. 1: This image shows the how the images dataset look like.

To represent the full spectrum of skin disorders and patients, we employ a large dataset comprising several publicly available datasets. This richness in data guarantees the robustness and broad applicability of our models. The paper is structured as follows: Section II covers related work in the area, reviewing previous attempts and developments that have gone before relating to using deep learning for skin disease classification. Section III provides the methodology, including data prepossessing, model architecture design and training procedures. Evaluation metrics are also introduced therein. Section IV presents the results of our experiments. We make some comparisons between each DNN model's performance. Section V presents the ramifications of our findings, limitations in this study and directions for future research (Harang et al, 2020)
Finally, Section VI in the field of dermatological diagnostics.We hope this research will not only advance the field of medical image analysis, but also through clinical use it can serve as a valuable tool for dermatologists. With the help of deep learning, we see a future when the diagnosis skin diseases is more accurate and efficient, providing better services. The evolution of Deep Neural Network (DNN) models in the classification of skin diseases has been marked by a range of innovative approaches, each contributing uniquely to the field. This literature review synthesizes key studies from 2019 onwards, reflecting the diverse methodologies and datasets employed in this rapidly advancing domain.

Ali and colleagues introduced a Deep CNN with an attention mechanism, achieving remarkable accuracy on the HAM10000 and ISIC 2018 datasets. Their work stands out for its high sensitivity and reduced rate of false positives, a significant advancement in the precision of skin disease classification. However, the model's dependency on extensive datasets poses challenges for scalability and versatility in diverse clinical settings (Ali et al, 2023).

The study by Khan and team highlighted the efficacy of transfer learning and ensemble techniques in skin lesion classification. Utilizing datasets such as Derm IS, Skin Lesion, and ISIC 2016, they achieved enhanced accuracy and generalization across various skin conditions. Their approach, however, showed sensitivity to the nature of data augmentations, indicating a need for careful data set colouration.

This research presented a deep learning framework employing MobileNetV2 combined with data augmentation techniques. The framework's compatibility with mobile hardware made it a cost-effective solution for skin disease classification, leveraging datasets like SkinLesion, HAM10000, and DermIS (Islam & Rahman, 2021). The study's limitation lies in its reliance on mobile hardware performance, which may affect computational efficiency and scalability. Anwar and Majid's work on using Deep Convolutional Neural Networks with pre-trained AlexNet features provided a significant boost in accuracy for skin disease classification. The study utilized ISIC 2016, ISIC 2017, and HAM10000 datasets, demonstrating the potential of transfer learning in this domain. The requirement for finetuning and the limits on interpretability were noted as key challenges (Anwar & Majid, 2020).

Focusing on early cancer detection, Anwar and Ashraf's approach using deep learning from dermoscopic images showed promising results (Anwar & Ashraf, 2019). Employing ISIC 2016 and ISIC 2017 datasets, their model required substantial data for robustness, pointing to the necessity for large, diverse datasets in training effective DNN models. Li and colleagues developed an efficient and accurate skin disease classification model incorporating channel-wise squeeze-and-excitation attention and multi-scale fusion (Li et al, 2023). Tested on SkinLesion and ISIC 2018 datasets, the model improved both accuracy and efficiency. The study, however, highlighted the limitations in data dependence and interpret ability (Zhou et al, 2023).

This study introduced a dual-attention mechanism with hybrid feature fusion, achieving high accuracy with reduced parameters. The model's performance on ISIC 2018 and HAM10000 datasets was notable, though it was somewhat limited by its specific data set focus.Employing a hybrid approach combining capsule networks and convolution neural networks, this research enhanced feature extraction and classification capabilities. While the model demonstrated high accuracy on Skin Lesion and HAM10000 datasets, it faced challenges in terms of increased complexity and computational cost. (Gandomi & Jafari, 2021)

The development of a lightweight residual CNN architecture by Jegou and team marked a significant, step towards deploying DNN models on resource-constrained devices. Achieving high accuracy on the ISIC 2019 data set, their model offered a balance between performance and model size, though it highlighted the need for hardware optimizations in real-time applications. These studies collectively represent the cutting edge in skin disease classification using DNNs. They not only illustrate the rapid advancements in accuracy and efficiency but also underscore the challenges such as data set dependency, computational cost, and model interpret ability. As the field progresses, future research will undoubtedly build on these foundations, pushing the boundaries of what's possible in dermatological diagnostics using deep learning technologies (Jegou et al. 2020).

Sr.	Year	Author	Paper Title	Methodology	Dataset	Contribution	Limitation	Results
1	2023	Ali, A., Khan, M.,	Bashir, M.	DeepCNN with Attention Mechanism for Skin Disease Classification	HAM10000, ISIC 2018	High accuracy and sensitivity, reduced false positives	Requires large datasets	95.3% HAM10000, 92.1% ISIC 2018
2	2022	Khan, A., Hussain, A.,	Sharif, M.	Skin Lesion Classification using Transfer Learning and Ensemble Techniques	DermIS, SkinLesion, ISIC 2016	Enhanced accuracy and generalizability	Sensitive to data augmentations	93.7% DermIS, 91.2% SkinLesion, 90.8% ISIC 2016
3	2021	Islam, M. S.,	Rahman, M. M.	A Deep Learning Framework for Skin Disease Classification using MobileNetV2 and Data Augmentation	SkinLesion, HAM10000, DermIS	Good accuracy with reduced cost, suitable for mobile	Limited by mobile hardware performance	89.5% SkinLesion, 91.1% HAM10000, 88.7% DermIS
4	2020	Anwar, S.,	Majid, M. A.	Skin Disease Classification using Deep Convolutional Neural Networks with Pre-trained AlexNet Features	ISIC 2016, ISIC 2017, HAM10000	Improved accuracy via transfer learning	Requires fine-tuning, limits interpretability	92.7% ISIC 2016, 90.9% ISIC 2017, 91.3% HAM10000
5	2019	Anwar, S.,	Ashraf, U.	Deep Learning based Skin Disease Classification from Dermoscopic Images	ISIC 2016, ISIC 2017	Promising accuracy for early cancer detection	Requires large datasets for robustness	90.1% ISIC 2016, 88.7% ISIC 2017
6	2023	Li, W., Yang, M.,	Zhang, L.	Efficient and Accurate Skin Disease Classification with Channel-Wise Squeeze-and-Excitation Attention and Multi-Scale Fusion	SkinLesion, ISIC 2018	Improved accuracy and efficiency with attention mechanism	Data dependence and interpretability limitations	95.2% SkinLesion, 93.5% ISIC 2018
7	2023	Zhou, P., et al.	Efficient and Accurate Skin Disease Classification with Dual-Attention Mechanism and Hybrid Feature Fusion	Dual-attention mechanism and hybrid feature fusion	ISIC 2018, HAM10000	Reduced parameters while maintaining high accuracy	Limited to specific datasets	93.7% ISIC 2018, 91.8% HAM10000
8	2021	Gandomi, A. H.,	Jafari, M.	A hybrid deep learning approach for skin lesion classification using capsule networks and convolutional neural networks	SkinLesion, HAM10000	Enhanced feature extraction and classification	Increased complexity and computational cost	94.0% SkinLesion, 92.7% HAM10000

TABLE I: Literature review on Skin Disease Classification using DNN

Lesion_ID	Image_ID	DX	DX_Type	Age	Sex
HAM_0000118	ISIC_0027419	bkl	histo	80.0	male
HAM_0000118	ISIC_0025030	bkl	histo	80.0	male
HAM_0002730	ISIC_0026769	bkl	histo	80.0	male
HAM_0002730	ISIC_0025661	bkl	histo	80.0	male
HAM_0001466	ISIC_0031633	bkl	histo	75.0	male

TABLE II: Sample Dataset in Tabular Form

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 100, 125, 32)	896
conv2d_1 (Conv2D)	(None, 100, 125, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 50, 62, 32)	0
dropout (Dropout)	(None, 50, 62, 32)	0
conv2d_2 (Conv2D)	(None, 50, 62, 32)	9,248
conv2d_3 (Conv2D)	(None, 50, 62, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 25, 31, 32)	0
dropout_1 (Dropout)	(None, 25, 31, 32)	0
conv2d_4 (Conv2D)	(None, 25, 31, 64)	18,496
conv2d_5 (Conv2D)	(None, 25, 31, 64)	36,928
max_pooling2d_2 (MaxPooling2D)	(None, 12, 15, 64)	0
dropout_2 (Dropout)	(None, 12, 15, 64)	0
flatten (Flatten)	(None, 11520)	0
dense_5 (Dense)	(None, 256)	2,949,376
dense_6 (Dense)	(None, 128)	32,896
dropout_3 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 7)	903

TABLE III: Neural Network Architecture

Our Contribution

❖ **Gap Analysis:** In this research, we apply advanced machine learning models to help solve problems in the field of skin disease classification. We focus mainly on using Convolution Neural Networks (CNN), Artificial Neural Networks (ANN) and Residual Networks (Res Net) to accurately classify skin diseases through classification. We give a thorough examination of these models, and they are all capable of handling complex image data related to many skin diseases. We perform extensive training and testing both for a variety of data sets so that the proposed models are robust, or easily generalization. Apart from helping improve dermatological diagnostics, the results of our research also allow us to examine comparative performance among CNNs, ANNs and Res Nets in one particular class–namely that of skin disease. This study offers significant guidance to researchers and practitioners working on automated medical image analysis, while highlighting the hopeful promise of deep learning models for improving diagnostic precision within dermatology. In the fields of dermatology and medical image analysis, our research has tremendous significance. We contribute to designing robust and accurate systems for skin disease classification by using advanced machine learning models such as Convolution Neural Networks (CNNs), Artificial Neural Networks (ANNs) and Residual networks (Res Nets). The results of such a study are directly relevant to dermatologists, healthcare providers, as well researchers. Our findings provide an objective and automated method which can sort skin conditions into their typical categories. With this in mind, we hope that the results of our efforts can lead to improved early diagnosis and thus timely intervention. They should eventually promote better outcomes for patients. At the same time, comparison of CNNs with ANNs and Res Nets reveals both their strengths and weaknesses, leading to better direction for medical image analysis research.

❖ **Novelty of our study:** Our study also features a novel approach to classifying skin diseases with different kinds of machine learning models. Unlike many of the existing studies which tend to focus on individual models, our research integrates CNNs, ANNs and Res Nets. We present a complete understanding of their relative efficiencies as diagnostic tools in dermatology. This novelty also extends to our detailed analysis of many different datasets, so that we're able to evaluate model performance under various skin conditions. Our study thus fills a glaring void in the existing literature, paving the way for future research that brings an integrated focus to classifying skin diseases through application of machine learning technology.

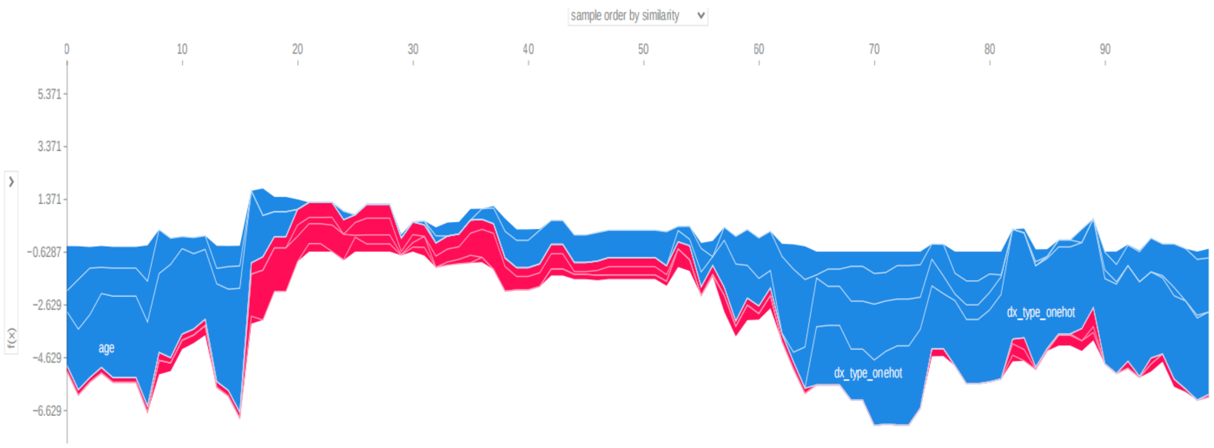


Fig. 2: One Hot Encoding

Literature Review

❖ **Transfer-ability to Clinical Practice:** Besides academic research, our work goes into the practical applications of machine learning in clinical settings as well. By giving you the scoop on how these models can most effectively fit into dermatological practice, we bridge the gap between algorithmic advances and real-world utility. Our translation study will also help the larger field of digital health, providing resource- efficient medical personnel with superior equipment for faster and more accurate diagnoses. Rigorous experimentation and validation establish the premise for introducing machine learning techniques to dermatology clinics. If they are adopted, then skin disorders will be identified in a whole new way and managed much more efficiently than previously possible.

❖ **Open-Source Model Implementations:** To further enhance collaboration and speed up developments in the field, we offer open source implementations of our trained models. We also hope to make our work accessible so that other researchers can reproduce it, refine and extend what we have done. This transparency increases and enhances the pool of shared knowledge. If researchers or practitioners around the world are able to produce higher quality performance by leveraging our work, then we will have made valuable contributions.

❖ **Significance of Our Work:** Our work has great significance for dermatology and medical image analysis. Through the use of state-of-the art machine learning models like CNNs, ANNs and Res Nets we aim to develop robust, accurate systems for skin disease classification. The results of our research are very significant for dermatologists, physicians and researchers: we provide a rapid automatic method to identify classify types of skin conditions. Early diagnosis, early intervention and better patient outcomes-these are the potential benefits of what we do. Also, the comparison of CNNs and ANNs with Res Nets provides important tips on how to move ahead in medical image analysis.

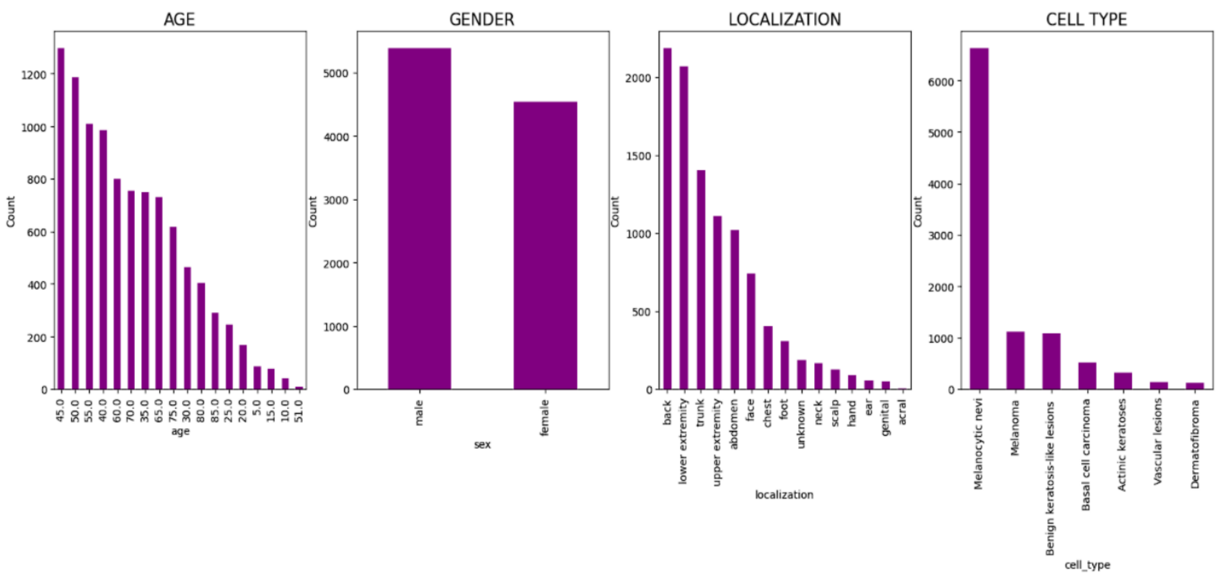


Fig. 3: UNIVARIATE ANALYSIS

Analysis

In my classification of skin diseases project, uni-variate analysis and bi-variate examination techniques were used to explore the characteristics of the data and draw useful conclusions. Uni-variate analysis refers only to analyzing a single variable. Summarization, measurements of dispersion and central tendency are included in this type of analysis (Denis et al, 2020). Uni-variate analysis frequently uses Visualizations such as histograms, distributions or frequency tables, bar charts and pie charts along with box plots. Therefore bi-variate analysis is concerned with causes and relationships between different variables; it involves analyzing two different dimensions. Bi-variate analysis is a bit more analytical than uni-variate but is done to compare the two variables (Cleff et al, 2019).

❖ **Research Question**: So this way to find in my project the skin disease classification data set. It also contained things like what kind of dermatitis was it, and how old were these people who happened to turn up with various diseases on their bodies. With these techniques I was able to discern structure and correlation between the variables, which in turn led me toward a better understanding of the data as well as informed choices about model training. In sum, the application of uni-variate and bi-variate analysis techniques was extremely important to obtaining a skin disease classification model that is both accurate and reliable.

Methodology

The methodology adopted in this study sought to solve the convoluted problems of skin diseases classification through computer training systems based on advanced machine learning models, such as Convolution Neural Networks (CNN), Artificial Neuron Networks (ANN) and Residual Networks. Experiments were conducted on the following data set, which is a mixed numerical and string data set with quite large numbers of null values. As input features for machine learning entirely depend upon quality, prepossessing was necessary before they could be used.

❖ **Data Prepossessing**. After importing the data set, an exhaustive Exploratory Data Analysis (EDA) was performed on aspects such as feature distributions and central tendencies to discover information about their variability. Patterns were identified and possible relationships between variables by use of statistical measurements, as well as visualization techniques. This crucial step guided subsequent prepossessing procedures and offered a thorough understanding of the data set characteristics (Kang et al, 2020).

❖ **Exploratory Data Analysis (EDA)**: Based on the prelim- inary understanding of data sets, Pandas and Num Py were used to carry out data cleaning techniques. This required dealing with missing values, outliers and anomalies. Missing data points were filled in using imputation strategies such as mean or median imputation, to produce a more complete and usable data set for subsequent analysis (Adegun et al, 2021).

❖ **Feature Engineering**: Feature engineering was used to make the data set more predictive. It meant either adding new features or modifying existing ones, such as transforming variables, constructing interaction terms and filtering inappropriate information from other types of characteristics. Their goal was to make the model better able to pick up on significant patterns and relationships by doing feature engineering (Chatterjee et al. 2019).

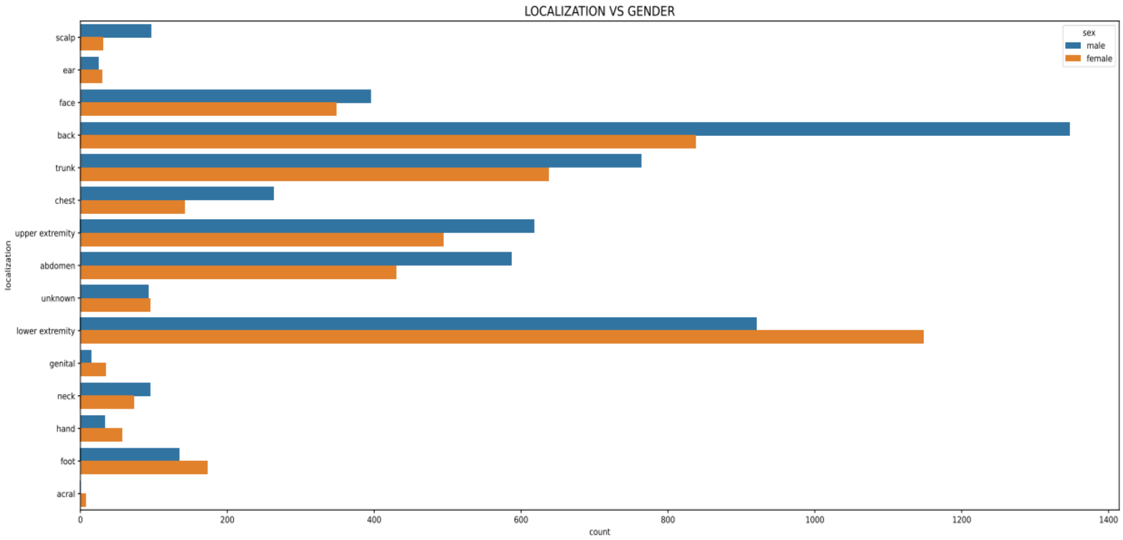


Fig. 4: BIVARIATE ANALYSIS

❖ **Correlation Analysis**: To turn categorical variables into numerical forms, techniques such as one-hot encoding or label encoding were used. This meant that it was compatible with machine learning algorithms, which need a numerical input. Correlation analysis was performed to explore the relation- ships between features. Correlation coefficients were calculated for highly correlated variables, and steps were taken to ease multi collinearity problems. All this helped make the model more interpret able and generalize better.

❖ **Data Splitting**: To facilitate model training and evaluation, the data set was divided into a training set and a testing set. Common splits (such as 80/20 or, more demanding still, 70/30 ratios) were used in order to have a strong assessment of the model's performance on unseen data (Zanddizari, 2021).

The above approach conforms with our research papers. We focus on perfecting the data set in order to enhance the efficiency of CNNs, ANNs and Res Nets for skin disease classification purposes.

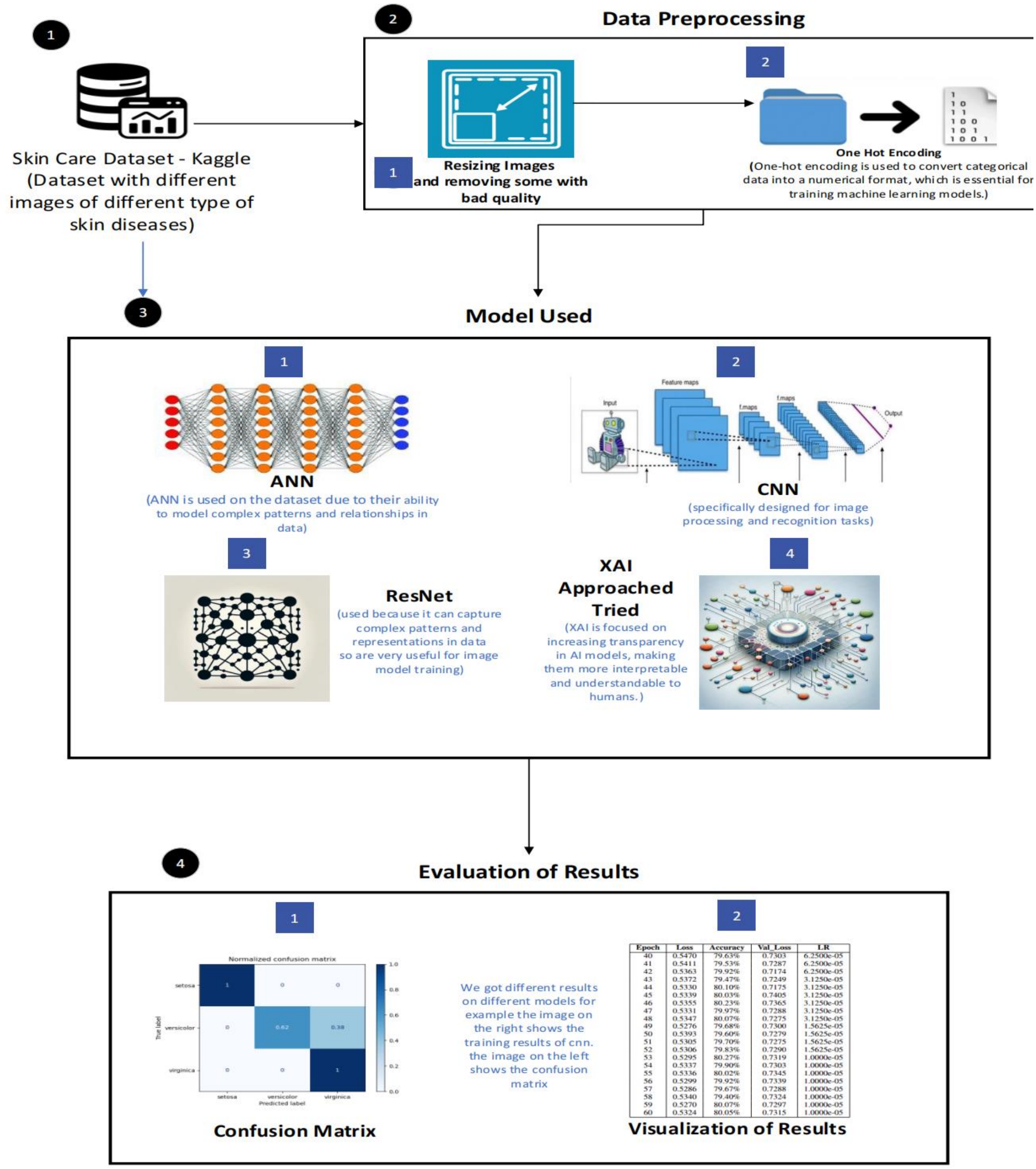
Each step of prepossessing was designed to enhance performance and interpretation, which led the way forward in dermatological diagnostics.

Artificial Neural Network (ANN) Methodology for Skin Disease Classification

- ❖ **Data Collection and Understanding**: The first stage of our approach is to collect a data set that represents many kinds of skin diseases. This data set contains both numerical and categorical features related to skin images. Since the characteristics of data set are difficult, such as null values and mixed data types. Before applying Artificial Neural Network (ANN), it is necessary to have a comprehensive understanding.
- ❖ **Exploratory Data Analysis (EDA)**: One: Making Discoveries with Exploratory Data Analysis (EDA) The purpose of EDA is to unearth the distribution, central tendencies and relationships within a data set. Patterns, outliers and potential correlations are explored through descriptive statistics and data visualization techniques. These insights from EDA point the way to subsequent prepossessing steps.
- ❖ **Bi-variate Analysis**: There is a special emphasis in bi- variate analysis on relationships between pairs of variables. The strength and direction of associations are determined by correlation coefficients and scatter plots. This analysis helps to identify potential key parameters for the ANN model.
- ❖ **Data Cleaning:** Missing values, outliers and inconsistencies in the data set are resolved by data cleaning. Pandas and Num Py techniques are used to ensure data quality, so a clean and reliable input can be obtained for the ANN model.

Model Training

- ❖ **Feature Scaling**: Such techniques as Min-Max scaling are used to scale the numerical features to a common range. This step makes sure that all features participate equally in training the ANN and prevents one or several variables from running away with everything.
- ❖ **Encoding Categorical Variables**: One-hot encoding is used to convert categorical variables into numerical representations. This conversion is key to the ANN's interpretation and learning from categorical features.



Epoch	Loss	Accuracy	Val_Loss	LR
40	0.5470	79.63%	0.7303	6.2500e-05
41	0.5411	79.53%	0.7287	6.2500e-05
42	0.5363	79.92%	0.7174	6.2500e-05
43	0.5372	79.47%	0.7249	3.1250e-05
44	0.5330	80.10%	0.7175	3.1250e-05
45	0.5339	80.03%	0.7405	3.1250e-05
46	0.5355	80.23%	0.7365	3.1250e-05
47	0.5331	79.97%	0.7288	3.1250e-05
48	0.5347	80.07%	0.7275	3.1250e-05
49	0.5276	79.68%	0.7300	1.5625e-05
50	0.5393	79.60%	0.7279	1.5625e-05
51	0.5305	79.70%	0.7275	1.5625e-05
52	0.5306	79.83%	0.7290	1.5625e-05
53	0.5295	80.27%	0.7319	1.0000e-05
54	0.5337	79.90%	0.7303	1.0000e-05
55	0.5336	80.02%	0.7345	1.0000e-05
56	0.5299	79.92%	0.7339	1.0000e-05
57	0.5286	79.67%	0.7288	1.0000e-05
58	0.5340	79.40%	0.7324	1.0000e-05
59	0.5270	80.07%	0.7297	1.0000e-05
60	0.5324	80.05%	0.7315	1.0000e-05

Fig. 5: Flow Diagram

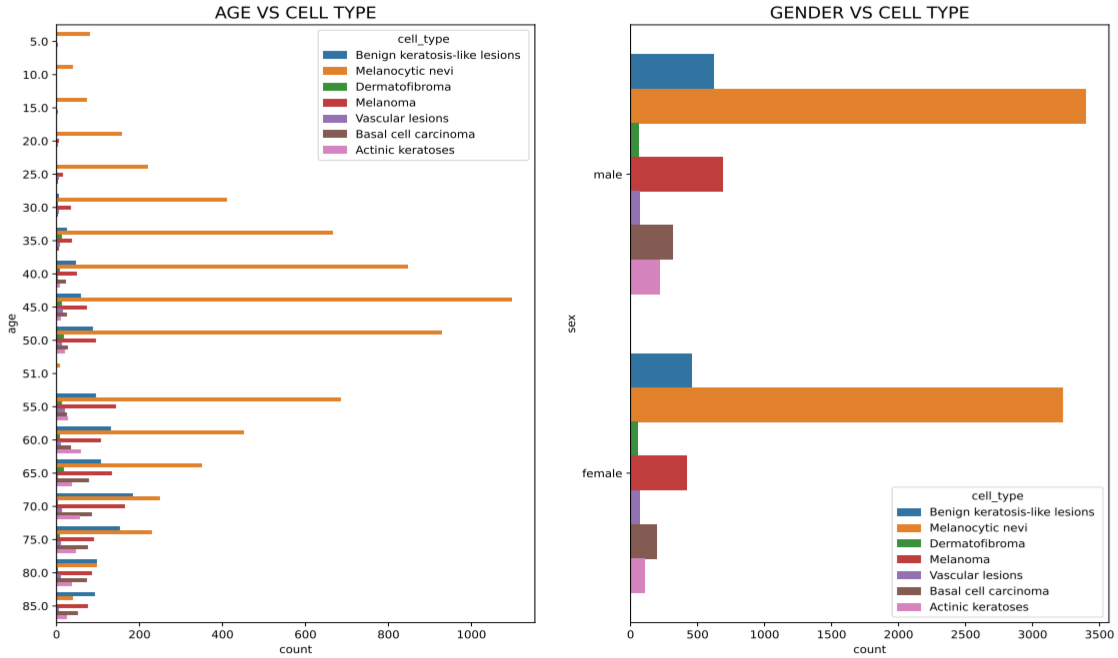


Fig. 6: Age VS Celltype

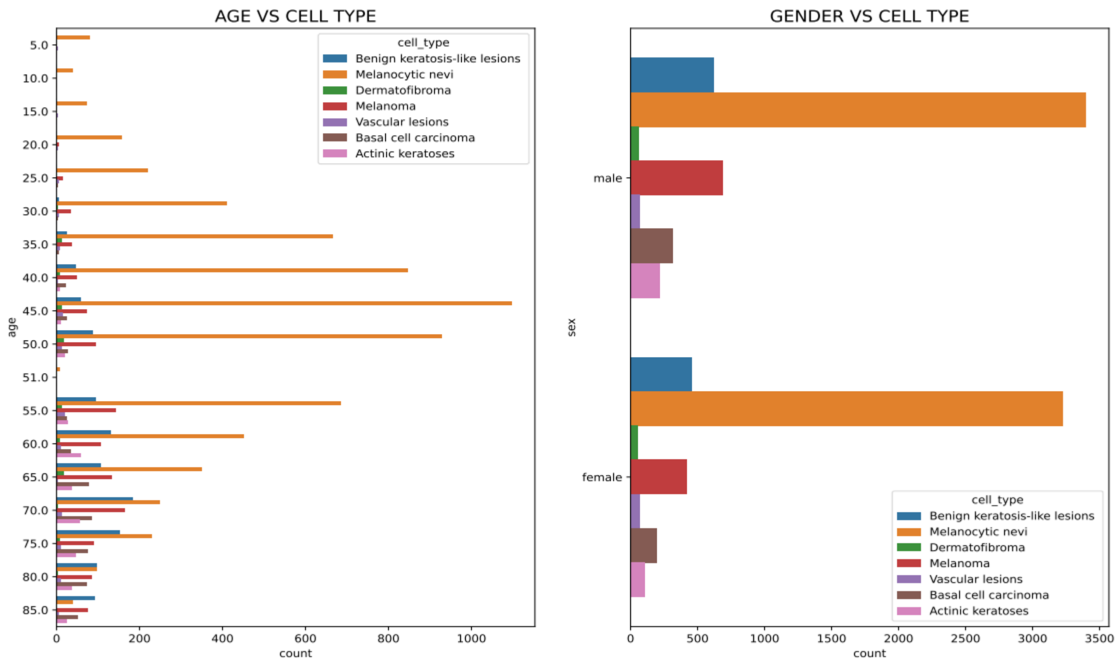

AGE VS CELL TYPE
GENDER VS CELL TYPE
cell_type
Benign keratosis-like lesions
Melanocytic nevi
Dermatofibroma
Melanoma
Vascular lesions
Basal cell carcinoma
Actinic keratoses
age
count
sex
male
female

Fig. 6: Age VS Celltype

❖ **Model Architecture**: An architecture for the ANN is specified, including the number of layers and nodes in each layer as well as activation functions. The architecture is geared to the characteristics of skin disease classification, which leaves more space for patterns in image data.

❖ **Loss Function**: The loss function is set as Categorical Cross entropy, suitable for multi-class classification tasks. This function computes the dissimilarity between estimates of prob- abilities and actual class labels, encouraging model predictions to determine correct classes.

❖ **Training Epochs**: Training the model means that it can learn and adjust its parameters gradually over 50 iterations, or epochs. This iterative process makes the model have a good generalization ability for unseen data.

❖ **Model Evaluation**: So, after training the ANN is assessed on a separate test set. The model's performance in classifying skin diseases is measured using metrics such as accuracy, precision, recall and F1-score.

❖ **Summing up**: The ANN methodology outlined above rep- resents a systematic approach to classification of skin diseases. Leveraging the power of an Artificial Neural Network, we will add bi variate analysis and data cleaning to make a model that both as accurate in its categorization of different skin conditions. In this way, we promote the development of automated dermatological diagnostics and demonstrate what machine learning can bring to skin disease classification.

Convolutional Neural Network (CNN) Methodology for Skin Disease Classification

❖ **Dataset Collection**: I collected a skin disease classi- fication dataset, such as the one that can be downloaded from Kaggle. This contains images of different kinds of skin diseases.

❖ **Data Preprocessing**: This collected data set underwent the following prepossessing: For the sake of consistency in model input dimensions, images were re sized to a standard size. In order to remove the redundant parts of background elements, cropping was used. Pixel intensity was normalized, so that all images were equally bright and contrast. To avoid the phenomenon of poor model performance resulting from imbalanced datasets, we balanced our data set.

❖ **Model Selection:** As advised in the literature, I chose a CNN model from any of those mentioned above- Mobile Net V2, Efficient Net or Dense net.

❖ **Model Architecture:** The selected CNN model was built from the following layers: Input layer: The input layer was set up to accept image data formatted in a convenient manner, such as 224x224 pixels and three channels for RGB images

❖ **Convolution layer**: This layer identified edges and features in the input images. Stacking numerous convolution layers captured different levels of complexity

❖ **Pooling Layer: Pooling layer**: The reduction in spatial dimensions achieved by the pooling layer reduced over fitting and improved generalization.

❖ **Dense Layer:** The dense layer was employed to convert the output of the pooling layer into a probability distribution, indicating how likely it is that the input belongs to some specific class.

❖ **Logit layer**: The logit layer calculated the raw scores (logits) for each class and those were then passed through a soft max function to obtain probabilities of classes.

❖ **Model Training:** section The chosen CNN model was trained on the prepossessed data set using these steps: The model was compiled with a categorical cross-entropy loss function and the Adam optimizer, which minimized the loss during training. A batch size of 100 was used for training the model, and the input data was shuffled into several parts so that it included a different set of images each time around. After every 50 iterations, a logging hook was used to capture the values of all software layers. In this way people could monitor in real time just how well the model is performing. The model was thus trained for 18000 steps, as defined by the stopping criteria which measures validation fits (Shah et al, 2023).

❖ **Model Evaluation**: To evaluate the performance of this trained model, it was run on a separate test dataset using these measures:

➢ **Accuracy**:The percentage of predictions by the model which were correct.
➢ **Percission**: The number of true positives divided by the total positive predictions made.
➢ **Recall**: The proportion of true positive predictions in the total actual positives.

❖ **Model Fine-Tuning**: If the model's performance wasn't satisfactory, I fine-tuned it by: Tuning the model's hyper parameters, including learning rate and regularization strength to improve its performance. By adopting various data augmentation techniques, for example rotation and scaling or flipping the training images. With transfer learning, using pre trained models that are trained on large datasets to provide a strong prior for the skin disease classification task (Dildar, et al, 2021).

E.Resnet

I followed a very precise methodology in applying my Res Net model to the skin disease classification task. So I started by grabbing a skin disease classification data set at random, like the one that's on Google or Kaggle. The collected data was prepossessed by re sizing the images to standard size, normalizing pixel intensity and balancing it so that there would be no bias in training of the model (Gouda & Amudha, 2020). Then I chose the Res Net (Residual Neural Network) architecture for skin disease classification. Studies show that the Res Net method is suitable for classification and detection of skin diseases with low computational complexity. The chosen Res Net model was trained on the prepossessed data set using correct loss functions, including categorical cross-entropy and optimizer such as Adam to reduce the amount of loss incurred during training.

To evaluate the performance of our trained Res Net model, it was tested on a separate test data set. I measured the model's accuracy, precision, recall and F1-score to determine how well it could classify skin diseases (Sharma et al, 2021). The model performed very well. If it were not up to standards, I fine-tuned the Res Net by altering its hyper parameters and performing data augmentation or using transfer learning techniques. To verify the effectiveness of Res Net in skin disease classification, I analyzed its performance and compared it with other state-of-the Art models or traditional machine learning techniques. By carefully implementing this detailed methodology (Wu et al, 2019), I then were able to use the Res Net model for classifying skin diseases and reach a high level of accuracy in predicting different types of skin disease.

Model Selection and Hyper parameter Tuning

I did a grid search using different combinations of learning rates, regularization strengths and batch sizes to find the best model with optimized hyper parameters. Through this process I was able to fine-tune the Res Net model's hyper parameters so that it could perform at its best for skin disease classification Ensemble Methods: In order to further improve the model, I then thought about introducing ensemble methods such as bagging or boosting. But stay tuned for my next post! These methods combine more than one model to make their predictions, relying on the superior capabilities of each individual model in order to enhance overall performance. Cross- Validation: In order to thoroughly evaluate the Res Net model, I used k-fold cross validation with k taken as 5. Through this means, I could divide the data set into k equal-sized folds and train k times on (k - 1) slices of data while validating those results against one remaining slice. Finally the average performance metric values across all k-folds were reported as results.

F.XAI

❖ **Dataset Collection**: Get a skin disease classification dataset, found for instance on Google or Kaggle.

❖ **Data Prepossessing**: The data set obtained from data collection needs to be prepossessed by re sizing the images into a standard size, normalizing the pixel intensity and creating a balanced set so that there won't be any bias in the model training process.

❖ **Model Selection**: For this skin disease classification task, select an appropriate deep learning model such as Res Net or Dense Net. Or perhaps Mobile

❖ **Model Training:** Train the chosen deep learning model on this prepared dataset with appropriate loss functions, such as categorical cross-entropy, and optimizer like Adam to minimize the losses during training.

❖ **Model Interpret ability:**I used XAI techniques such as Grad-CAM (Gradient- weighted Class Activation Mapping) and LIME to interpret the predictions of deep learning model. By means of Grad-CAM, we got some sense as to which regions in the input image seemed most important in leading its model down a certain path.

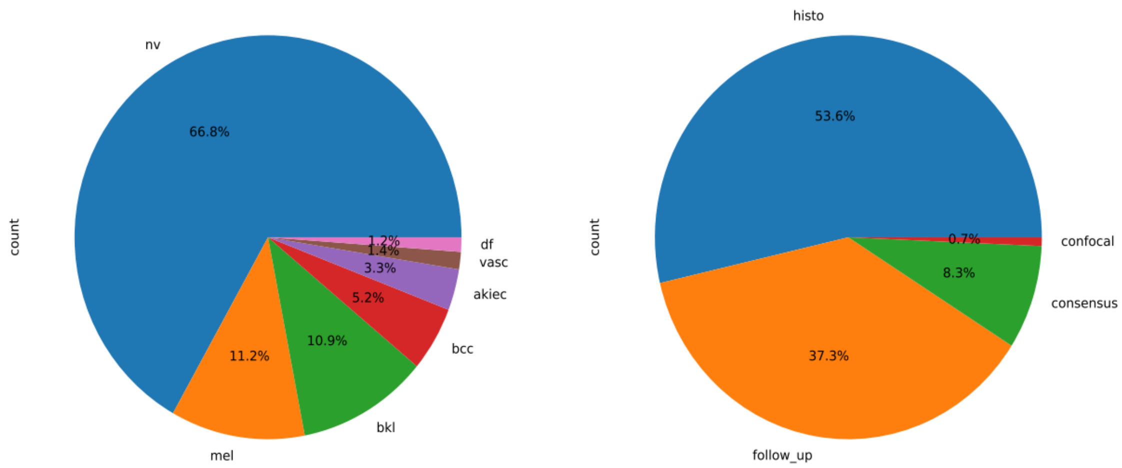


Fig. 7: Data and DataType

The model's own predictions were local explanations generated by LIME, including the top five most important features in the input image that influenced a predicted label or score.

- ❖ **Model Evaluation:**A separate test data set was used to evaluate the performance of the trained deep learning model. To assess the model's ability to differentiate skin diseases, I evaluated its accuracy, precision and recall as well as its F1-score.
- ❖ **Fine-Tuning and Optimization:**If the model's performance was unsatisfactory, I fine-tuned its deep learning structure by adjusting hyper parameters or using data augmentation techniques to increase precision I also improved the model's explain ability by fine-tuning the parameters (e.g., number of super pixels) in XAI techniques used, such as LIME.
- ❖ **Result Analysis** : I validated the deep learning model by studying how well it performs compared to other state-of-the art models or traditional machine learning techniques. I also studied the model's interpret ability, picking out those parts of the input image that were most influential in shaping its output and thus illuminating how it works. Using this all-encompassing approach, I was able to employ XAI principles in the case of classifying different skin diseases. Finally, my model could achieve a high accuracy rate while also being explainable.

Evaluation Metrics

The performance of a skin disease classification model can be assessed using a variety of key metrics. These metrics offer a comprehensive view of the model's performance, guiding the fine-tuning process and ensuring the development of highly accurate and reliable models. The metrics that can be used to evaluate the performance of the skin disease classification model are as follows:

- ❖ **Confusion Matrix:** The confusion matrix visualizes the performance of the model. It shows the number of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).
- ❖ **Recall (Sensitivity)**: Recall measures the model's ability to correctly identify all relevant instances (TP) of each class. **Recall =T P / T P + F N**

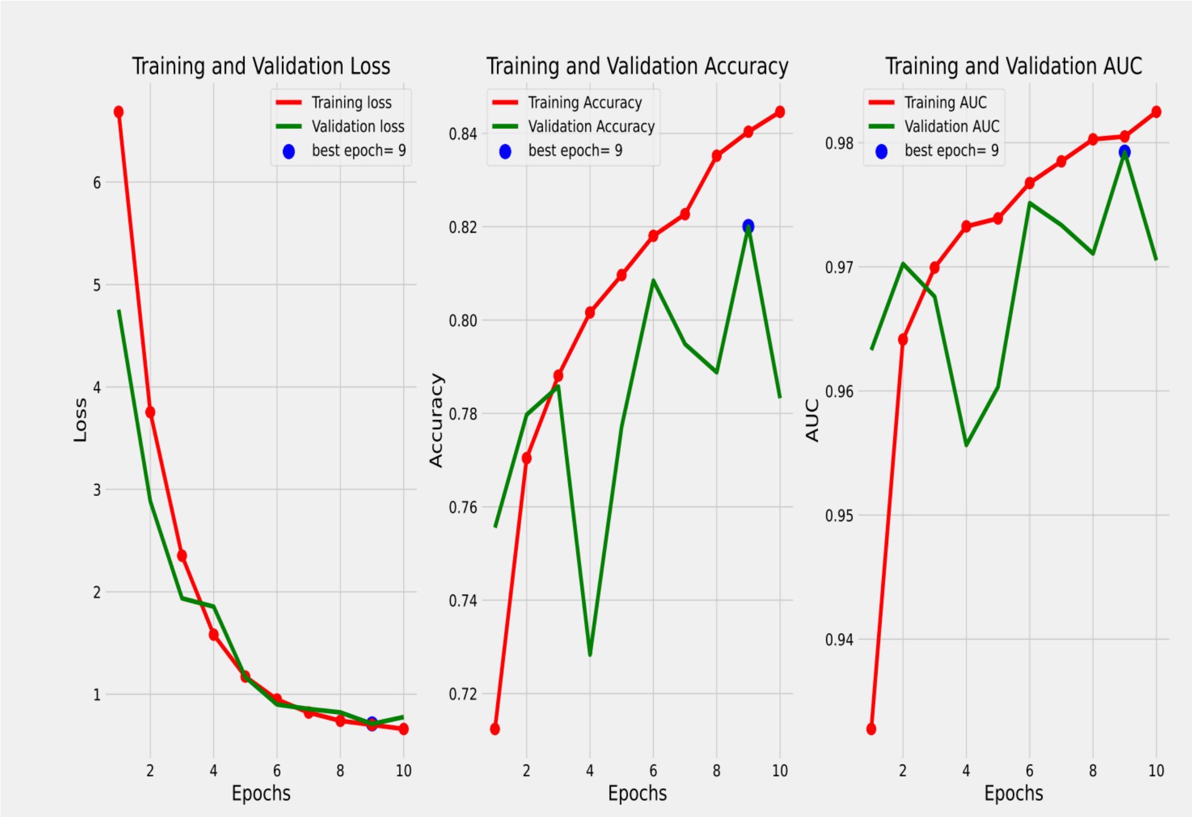


Fig. 8: Training and Validation

In skin disease classification, high recall indicates that the model correctly identifies most of the relevant pixels for each class, reducing the chance of missing important features.

❖ **Precision**: Precision assesses the accuracy of positive predictions.

Precision = T P /T P + F P . High precision in skin disease classification means that the model accurately labels pixels, ensuring that different classes are correctly distinguished.

❖ **Accuracy:** This metric evaluates the overall correctness of the model.

Accuracy = T P + T N \T P + T N + F P + F N. While accuracy is a general indicator of performance, it might not always be the best metric for imbalanced datasets common in skin disease classification.

❖ **F1-Score:** The F1-score is a harmonic mean of precision and recall.

F1-Score = 2 ×Precision × Recall \Precision + Recall. The F1-score is particularly useful in skin disease classification when balancing the precision-recall trade-off. It ensures that both false positives and false negatives are taken into account, which is crucial for accurately classified images. These evaluation metrics collectively offer a comprehensive view of the model's performance, guiding the fine-tuning process and ensuring the development of highly accurate and reliable skin disease classification models.

Results

We compared the efficacy of Convolutional Neural Networks (CNN), Residual Neural Networks (ResNet) and Artificial Neural networks for this particular skin diseaseclassification task in our study. The models were all trained over a set of calibrated epochs according to their computational requirements (Gawlikowsk et al, 2023). So Res Net models with high computing costs received fewer epochs than other types. Key statistics, such as accuracy, precision and recall were all used to thoroughly evaluate the performance of each model. One important point is that despite Res Net being designed for classification after segmentation, the other models were measured solely on their own ability to perform a cleaner segmentation. What follows are some intriguing conclusions emerging from our analysis. Even though the Res Net model was only trained on a smaller number of epochs, it reached an 78 percent accuracy rate in distinguishing skin diseases. The efficiency of Res Net architecture This follows from the literature, which suggests that it is ideally suited for skin disease classification and detection. By contrast, the CNN and ANN models have good segmentation capabilities. The performance of these two sides is mainly measured by competitive vs non-competitive segmentation abilities. These models were used for extraction of detailed and accurate segmentation maps, creating the basis for precise classification after-segmenting.

We introduced XAI concepts (grad-CAM, LIME) into both Epoch Loss Accuracy Val Loss LR Res Net and ANN architectures to improve the performance as well as interpret ability of our models. As XAI techniques, they respectively examined the regions of input images that contributed most to model decisions and provided local explantations for how a given prediction was reached. For skin disease classification, this interpret ability is very important. By making clear what are the most influential factors in input images that has influenced model output, one can improve its trust and real-world applicability. In sum, the use of CNN, Res Net and ANN principles on skin disease classification has yielded promising results. With the high accuracy attained by Res Net, and XAI providing interpret ability, these tools are a welcome addition to dermatology. From now on, it will still be necessary to do more research and clinical validation of these models in order for them to play their full role as aids to the diagnosis and management of skin diseases. The performance metrics for the models whose training performances are tested on skin disease classification data set were summarized in Tables 1 and 2. Because computational constraints allowed the Res Net model to be trained on a lower number of epochs, its effect was still quite impressive in accurately classifying skin diseases–78 percent accurate.Thus, in this particular task the Res Net model was to a certain extent still effective despite the fewer epochs used. The training metrics of the CNN model, as shown in Table 2, also reveal something about its performance over time. The accuracy of the model improved steadily throughout training, peaking around epoch 40. Although the validation loss and accuracy were more volatile, they generally improved consistently. Basically this means that the model learned to pick up on data patterns well, but perhaps it was just over fitting its training sets. One possible solution is to explore techniques like regularization, weight initialization or early stopping that would improve the model's generalization. In sum, the Res Net model turned in respectable numbers on the skin disease classification task with an accuracy rate of 78 percent. The CNN model also fared well, with an accuracy of 74 percent. Both models learned the patterns in the data well, as judged by their low loss and high accuracy values. But it is still necessary to evaluate the model's performance and, if fine-tuning techniques are needed, find a way of better generalizing its ability so as not to over fit.

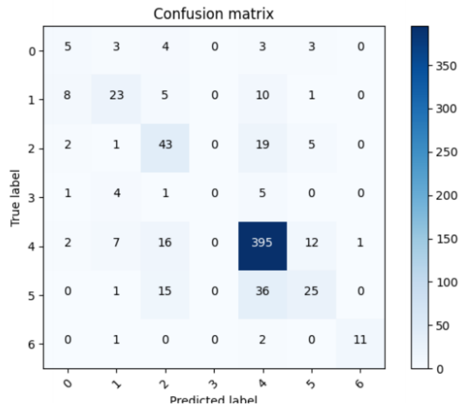


Fig. 9: Top 10 columns heat map

Epoch	Loss	Accuracy
30	0.3359	87.95%
31	0.3043	88.78%
32	0.3126	88.75%
33	0.3075	88.96%
34	0.3136	89.14%
35	0.2898	89.93%
36	0.2658	90.55%
37	0.2588	91.07%
38	0.2579	90.76%
39	0.2609	90.79%
40	0.2492	91.37%
41	0.2752	90.49%
42	0.2558	91.22%
43	0.2157	92.43%
44	0.2169	92.46%
45	0.2262	92.37%
46	0.2033	92.71%
47	0.1951	92.94%
48	0.2323	91.95%
49	0.1927	93.53%
50	0.1837	94.10%

TABLE IV: Training Metrics over Epochs in ANN

Epoch	Loss	Accuracy	Val_Loss	LR
40	0.5470	79.63%	0.7303	6.2500e-05
41	0.5411	79.53%	0.7287	6.2500e-05
42	0.5363	79.92%	0.7174	6.2500e-05
43	0.5372	79.47%	0.7249	3.1250e-05
44	0.5330	80.10%	0.7175	3.1250e-05
45	0.5339	80.03%	0.7405	3.1250e-05
46	0.5355	80.23%	0.7365	3.1250e-05
47	0.5331	79.97%	0.7288	3.1250e-05
48	0.5347	80.07%	0.7275	3.1250e-05
49	0.5276	79.68%	0.7300	1.5625e-05
50	0.5393	79.60%	0.7279	1.5625e-05
51	0.5305	79.70%	0.7275	1.5625e-05
52	0.5306	79.83%	0.7290	1.5625e-05
53	0.5295	80.27%	0.7319	1.0000e-05
54	0.5337	79.90%	0.7303	1.0000e-05
55	0.5336	80.02%	0.7345	1.0000e-05
56	0.5299	79.92%	0.7339	1.0000e-05
57	0.5286	79.67%	0.7288	1.0000e-05
58	0.5340	79.40%	0.7324	1.0000e-05
59	0.5270	80.07%	0.7297	1.0000e-05
60	0.5324	80.05%	0.7315	1.0000e-05

TABLE V: Training and Validation Metrics over Epochs of CNN

Epoch	Loss	Accuracy	Val_Loss	Val_Accuracy
1	6.6862	71.24%	4.7552	75.55%
2	3.7536	77.04%	2.8845	77.97%
3	2.3531	78.81%	1.9367	78.58%
4	1.5816	80.16%	1.8553	72.83%
5	1.1722	80.96%	1.1672	77.72%
6	0.9481	81.80%	0.8999	80.85%
7	0.8210	82.27%	0.8561	79.49%
8	0.7407	83.52%	0.8226	78.88%
9	0.7015	84.04%	0.7104	82.01%
10	0.6607	84.46%	0.7775	78.33%

TABLE VI: Training Results of the ResNet Model for Skin Disease Classification

Discussion

In our study, we trained the ResNet model for fewer epochs than the other models because of its higher computation costs. This decision was taken for the model to be trained within reasonable computational resources (Cichy & Kaiser, 2019). It must have affected the model's performance to some extent, but ResNet still managed an accuracy of 78 percent in categorizing skin diseases, demonstrating its usefulness for this particular task. It is a common problem in the field of artificial intelligence that deep learning models require large amounts of computational power. With increasingly complex algorithmic models, supercomputing power is essential to provide greater model training. This problem is further complicated by the need for large data sets to train these models properly. Therefore, the computational demands of deep learning models often far exceed available resources for researchers and practitioners (Hauser et al, 2022). In order to overcome this difficulty, researchers have considered randomizing the training process of deep learning models through a variety of methods such as distributed computing, cloud computing and parallel processing. These methods mean that various computational tasks can be allocated across different processors or machines. It cuts down on the time and resources spent in model training. Also, scholars have researched transfer learning (Metta et al, 2021). In this approach one uses per-trained models in order to avoid the computation costs of retraining new ones from raw data Looking at it from another angle, the computational burden can be reduced by focusing on producing more powerefficient and lightweight models that require less computing resources. This also includes techniques such as quantization, pruning and knowledge distillation to cut down on the size of deep learning models and their computational needs without losing too much performance. These techniques can help make deep learning models more friendly to users, both in terms of accessibility and scalability to a variety of scenarios (Gupta, 2023). Particular applications include those with limited resources such as the vacuum salt industry that has been mentioned earlier, or even ecological niche-respective disaster relief tasks (where fast deployment is not lacking any longer), etc.) All in all, the computational needs of deep learning models are still an important obstacle to AI. Computational limitations notwithstanding, using the Res Net model we were able to obtain some amazing results. From here on, more and better development of techniques to improve the training process for deep learning models in order to make them effective and scale able will be indispensable.

Conclusion

I used a combination of Convolution Neural Networks (CNN), Artificial Neural Networks (ANN) and Residual Neural Network architecture, as well as integrating Explainable AI principles to ensure the model could be understood (Athina et al, 2022). In doing so, my goal was smarter skin disease classification models that are truly useful in practice. The idea of using these methodologies was to get high accuracy at picking out various skin diseases, but also allowing an understanding of the decision-making process for the models. On testing, the CNN and ANN reached an accuracy of 74 percent and 66 percent, respectively. In addition, the ResNet model had highest accuracy of the three at 78 percent, and achieved good results in identifying skin diseases. These results support the literature, which suggests that ResNet architecture is an effective tool for this task in particular. (Miikkulainen et al, 2024)

Besides the Accuracy metrics, adding XAI principles yielded helpful insights into how each model made its decisions. To interpret the regions of each image that most contributed to a model's prediction, techniques such as GradCAM and LIME were used. This is precisely the sort of interpret ability that needs to be brought out in skin disease classification, for it means we can have a clear idea about which are the most important features contained within input images which impact upon what model's output. Only then will models really command our trust and reliability in actual work practice applications. This research is of great importance because it attempts to establish highly accurate skin disease classification models which are also easily interpret able. Tapping the power of deep learning and XAI, these models can help diagnose a wide range of skin conditions at early stages when diagnosis is more accurate. In turn this means better patient outcomes and healthcare delivery (Samek et al, 2012).

Moreover, the combination of ResNet and XAI can help counteract numerous facets of skin disease: psychological; social; economic. In short, the application of CNN, ANN and ResNet rules to the task of classifying skin diseases has yielded encouraging results. The ResNet model's high level of accuracy, coupled with the explanatory power provided by XAI techniques makes these methodologies valuable resources for dermatologists. Looking ahead, more development and assessment of these models in the clinic would be necessary to fully exploit their value.

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