A Review On Real Time Skin Disease Analysis, Segmentation and Classification

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Abstract

Skin is an extraordinary human structure. It often suffers from several far-famed and unknown diseases. According to dermatology, it is a regular practice to do extensive tests on patients to ascertain the kind of skin illness they have been afflicted with. The duration of time varies from one practitioner to the next, depending on their experience. Therefore, diagnosis of human skin diseases is the most unsure and sophisticated branch of science. it's been ascertained that the majority of the cases stay disregarded due to the shortage of higher medical infrastructure and facilities. Our work aims at providing an automated image-based method for diagnosing and categorizing skin problems that uses image processing and machine learning classification. With an easy-to-use User Interface. We have also added the segmentation image filter so that we can have better image analysis and accurate classified results.

Introduction

There are many disorders that can damage the skin because it is a complicated tissue. Skin disease diagnosis, however, is a difficult and complex process that needs significant testing and expertise. In addition, the lack of medical infrastructure and services causes many skin disease cases to go undiagnosed, which can result in complications and the spread of infection.

To solve this challenge, the authors suggest an automated image-based system for identifying and classifying skin issues. This approach makes use of machine learning classification and image processing, which offers a quick and accurate solution to identify and classify skin conditions. The authors want to develop a user interface that is simple to use and will facilitate rapid and precise diagnosis.

Skin conditions are more common, with melanoma being the most varied form of skin cancer and psoriasis impacting over 130 million individuals. In remote places, dermatophytosis is also common. It is essential to identify skin conditions early and take steps to minimize infection spread and complications. Early detection of the disease can be achieved by looking into the affected area.

The difficulty in developing an effective and reliable algorithm for detecting skin illnesses makes normalizing skin tone another problem. Skin photographs have a wide range of properties. The authors' goal is to address these problems in order to better understand skin disorders, treat them, and lessen the impact they have on both people and society.

The models we used in this project are the variants of ResNet, VGG and CNN.

For the segmentation part, the code defines a function which extracts the features that takes two arguments: input_dict, a dictionary containing binary masks of segmented regions of an image, and base_path, the base path where the images are stored. The function extracts a set of features from the segmented regions, including asymmetry, border irregularity, color variegation, diameter, and texture.

For each image in the input_dict, the function reads the corresponding image from the path, converts it to grayscale, and calculates the features from the segmented region of the image using various image processing techniques.

The calculated features are stored in a dictionary called features, where the keys are the image names, and the values are lists containing the calculated feature values. Finally, the function returns the features dictionary.

ResNet

ResNet, which stands for Residual Network, is an architecture for deep neural networks that was created to facilitate the training of extremely deep convolutional neural networks.

The first-place winner of the ImageNet and COCO 2015 competitions, it was unveiled by Microsoft Research Asia in 2015. Skip connections, often referred to as residual connections, are introduced by ResNet. These connections let the network avoid some layers and help the gradients flow more easily as it is being trained. The vanishing gradient problem that frequently happens with deep networks is lessened by the skip connections, which allow the construction of much deeper neural networks.

For many computer vision applications, including segmentation, object identification, and picture classification, ResNet has emerged as a popular and efficient design.

VGG

An image categorization task-specific convolutional neural network architecture is called VGG (short for Visual Geometry Group).

It was introduced in 2014 by the Visual Geometry Group at the University of Oxford, and its performance on the ImageNet classification challenge was state-of-the-art. A sequence of convolutional layers, followed by max pooling layers, and fully connected layers for classification are the building blocks of the VGG, which is distinguished by its uniformity and simplicity. The network is available in numerous variants with various depths and quantities of parameters, each bearing the names of the inventors, Simonyan and Zisserman. Many effective neural network architectures have been influenced by the VGG, a baseline architecture that has been widely employed for a variety of computer vision tasks.

CNN

In many applications for image and video recognition, convolutional neural networks (CNNs) are a sort of deep learning method. CNNs employ a hierarchical approach to pattern recognition, learning and recognising features at various levels of abstraction, starting with low-level features like edges and lines and progressing to higher-level features like forms and objects.

Layers that are pooled, completely connected, and used for convolutional neural networks make up CNNs. Applying a set of teachable filters to the input image or feature map allows convolutional layers to extract the necessary features. In order to avoid overfitting and increase computing efficiency, pooling layers downsample the feature maps and lower their dimensionality.

Problem Statement

- Nowadays, people are suffering from skin diseases. More than one hundred thirty million people are affected by Psoriasis. Skin cancer is swiftly growing over the last few decades, especially Melanoma, which is the most diverse type of skin cancer. Dermatophytosis rate is high especially in rural areas. If skin diseases are not treated at an earlier stage, then it may lead to complications in the body including spreading of the infection from one individual to the other. Skin diseases can be prevented by investigating the infected region at an early stage. So with our project, this can be solved.
- Normalizing the skin tone, so that it works for everyone.
- Another issue is The characteristics of the skin images are diversified, so that’s a challenging job to devise an efficient and robust algorithm for detection of skin diseases.

Literature Survey

[1] Opportunities and Challenges: Classification of Skin Disease Based on Deep Learning

Methodology :

In this Paper the Author aims to

- Provide a quick review of the classification of skin disease using Deep Learning to summarize the characteristics of skin lesions and the status of image technology.
- To study the characteristics of skin diseases and review the research on skin disease classification using deep Learning .
- Analysis of the study using datasets, data processing, classification models, and evaluation criteria.

Dataset Used :

The image effect of non-dermoscopic photographs can be influenced by the unpredictability of imaging conditions, such as shooting angle, light, and storage pixels. The table above is a collection of selected published datasets that include more than a dozen different types of skin conditions, with melanoma having the highest likelihood of occurring. However, the labeling of photographs is labor-intensive and time-consuming due to the lack of a unified standard for skin disease images, which significantly reduces the size of the current public datasets. Multiple datasets have thus been pooled for use in many investigations.

Pros and Cons :

Cons in the Current System of Skin Disease Classification :

- There is no strict correspondence between the symptoms and results of a disease and no clear boundary between the different diseases. Thus, the use of deep learning for disease diagnosis continues to require considerable effort.
- It is possible that humans could not truly understand how a machine functions, even though it is actually inspired by humans . Hence, whether or not patient care can be accepted using an opaque algorithm remains a point of discussion.
- A difficulty exists when the size of the dataset utilized in various skin cancer tests changes, which results in a change in the error rate value in the dataset. Since the error rate numbers are taken into account in many experiments, the absence of a standard dataset can result in major issues.
- There are many challenges involved since it is impossible to attain high reliability and low rate of time complexity at the same time. This is reflected in the training process and is influenced by conflicts between various standards.
- To make a convincing argument about a system's performance, the data used for evaluation are often too small. There aren't many images available for training for some minority and rare diseases. Numerous algorithms have shown prejudice toward minority groups so far, which might widen the gap between those who have access to health care and those who do not.
- Dermatology diagnosis is a difficult process that requires additional methods such as palpation, smell, temperature change, and microscopy in addition to image identification.

[2] Deep Learning has made considerable progress in the field of skin disease recognition. More effects and exploration in future can consider the following aspects:

- Establishment of standardized skin disease image dataset
- Interpretability of skin disease recognition: The development of deep learning for skin disease recognition depends on a highly nonlinear model and technology for parameter adjusting. The vast majority of neural networks, however, are "black box" models, making it difficult to comprehend how they make decisions internally. This "end-to-end" decision-making approach results in deep learning having minimal explanatory power. The outcomes of the model's diagnosis are less compelling due to the unclear internal logic of deep learning. The owner of the system could clearly understand the behaviour and boundaries of the system by using the interpretability research of skin disease classification, which would also guarantee the system's dependability and safety.
- intelligent skin disease diagnosis and treatment
- In order to address the rising number of patients with skin diseases and lessen the burden on the limited number of dermatologists, deep learning can be applied. One might anticipate that a deep learning-based skin disease recognition system will be made available to intelligent gadgets to better serve more people as mobile phones, mobile computers, and wearable technology become more and more popular.
- Users can upload their own images of the infected area to the cloud recognition system using a mobile device's camera and obtain the diagnosis findings whenever they want. Diagnosis recommendations and potential treatment options may be made available through straightforward communication with the "skin manager". Additionally, the "skin manager" could keep track of the user's skin condition and offer real-time treatment and protection advice.

Results and Conclusions:

The potential benefits of deep learning-based treatments for skin conditions are enormous, and they have the unrivaled advantage of easing the burden on medical resources and dermatologists' repetitive work. Since accurate detection is a laborious task, there is a growing need for a trustworthy automated detection method that both experienced and trainee doctors can use regularly during the diagnostic process. A thorough understanding of deep learning necessitates a breadth of expertise in engineering, information, computer science, and medical.

Deep learning is advancing quickly as a result of the above fields' ongoing progress and has caught the interest of many nations. It is clear that deep learning for the identification of skin diseases is a feasible technique in the near future thanks to more affordable solutions, software that can swiftly collect and usefully process huge amounts of data, and technology that can do what people cannot.

[3] Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images

Methodology :

In this paper the author studied different CNN algorithms for face skin disease classification based on the clinical images. First, from Xiangya–Derm, which is China’s largest clinical image dataset of skin diseases, the author established a dataset that contains 2656 face images belonging to six common skin diseases [seborrheic keratosis (SK), actinic keratosis (AK), rosacea (ROS), lupus erythematosus (LE), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC)]. Then the author performed studies using five mainstream network algorithms to classify these diseases in the dataset and compared the results. Then, they performed studies using an independent dataset of the same disease types, but from other body parts, to perform transfer learning on their models.

TABLE 2. Structures of the five models.

ResNet50	Inception V3	*DenseNet-121*	*Xception*	*Inception-Resnet V2*
Input layer 10*10*64, S=2, P=3*3, S=2, Out=75*75*64 ↓ **Conv1.x** [1*1*64, 3*3*64, 1*1*256]*3 Out=75*75*256 ↓ **Conv2.x** [1*1*128, 3*3*128, 1*1*512]*4 Out=38*38*512 ↓ **Conv3.x** [1*1*256, 3*3*256, 1*1*1024] *6 Out=19*19*1024 ↓ **Conv4.x** [1*1*512, 3*3*512, 1*1*2048] *3 Out=10*10*2048 ↓ **Global Average Pool** Out=1*1*2048 **Fully Connected** Out=1024 **Softmax** Out=6	**Input layer** 3*3*32, S=2, Out=150*150*32 ↓ **Conv1.x** 3*3*32, S=1, 3*3*64, S=1, P=3*3, S=2, Out=75*75*64 ↓ **Conv2.x** 3*3*80, S=1, 3*3*192, S=2, 3*3*288, S=1, Out=38*38**288 ↓ **3 * inception block** Out=19*19*768 **5 * inception block** Out=10*10*1280 **2 * inception block** Out=10*10*2048 ↓ **Global Average Pool** Out=1*1*2048 **Fully Connected** Out=1024 **Softmax** Out=6	**Input layer** 10*10*16, S=2, P=3*3, S=2, Out=75*75*16 ↓ **Dense_block1** [1*1, 3*3]*6 Out=38*38*160 **Transition layer1** 1*1, P=2*2, S=2, Out=38*38*160 ↓ **Dense-block2** [1*1, 3*3]*12 Out=38*38*304 **Transition layer2** 1*1, P=2*2, S=2, Out=19*19*304 ↓ **Dense-block3** [1*1, 3*3]*24 Out=19*19*448 **Transition layer3** [1*1, 3*3]*12 Out=10*10*448 ↓ **Dense-block4** [1*1, 3*3]*16 Out=10*10*595 ↓ **Global Average Pool** Out=1*1*1507 **Fully Connected** Out=1024 **Softmax** Out=6	**Input layer** 3*3*32, S=2, 3*3*64, Out=150*150*64 ↓ **Entry flow** [3*3, 3*3, P=3*3, S=2] *3 Concat each block by 1*1 Conv and S=2 Out=19*19*728 ↓ **Middle Flow** [3*3*728] *3 *8 ↓ **Exit flow** 3*3*728, *3*1024, P=3*3, S=2, 3*3*1536, 3*3*2048, Out=10*10*2048 ↓ **Global Average Pool** Out=1*1*2048 **Fully Connected** Out=1024 **Logistic Regression** Out=6	**Input layer** **(Stem)** 3*3*32, S=1, 3*3*32, 3*3*64, Out=147*147*64 ↓ **Mix** Mixed_3a Out=73*73*160 Mixed_4b Out=71*71*192 Mixed_5a Out=35*35*384 ↓ **5*inception-resnet-A** Out=35*35*256 **Reduction-A** Out=17*17*896 ↓ **10*inception-resnet-B** Out=17*17*896 **Reduction-B** Out=8*8*1792 ↓ **5*inception-resnet-C** Out=8*8*1792 ↓ **Global Average Pool** Out=1*1*1792 **Fully Connected** Out=1024 **Softmax** Out=6

Dataset Used :

[中南大学人工智能与机器人实验室 (csu.edu.cn)](#)

In this paper, the author established a dataset based on facial skin disease images, including 6 common skin diseases. The images in the dataset were obtained from Xiangya-Derm. These images and labels were rigorously reviewed by at least three experienced dermatologists. Xiangya-Derm consists of 150,223 clinical images from 543 different skin diseases. Each image is captured by digital camera and has a matched pathology and medical history. This construct was produced by the Department of Dermatology, Xiangya School of Medicine, Central South University. To the best of the author’s knowledge, it is the largest clinical image dataset of skin disease for computer-aided diagnosis (CADx). It is worth mentioning that the training set and the test set are divided according to different patients, which means that images of the same patient are prevented from appearing in both the training set and the test set. The author’s study was approved by the Ethics Committee of Xiangya School of Medicine, Central South University.

Results and Conclusions:

TABLE 3. Results of the model which have not been pre-trained by images of other body parts.

Net		BCC	LE	ROS	SK	AK	SCC	Average
Resnet50	Recall (%)	61.5	96.4	37.8	76.5	40.0	47.9	**56.7**
	Precision (%)	47.6	56.2	64.1	70.9	40.0	55.7	**55.8**
Incpetion V3	Recall (%)	63.1	95.2	37.0	76.5	46.7	51.0	**59.9**
	Precision (%)	39.4	62.0	55.3	61.9	43.8	66.7	**54.9**
Densenet-121	Recall (%)	70.8	92.9	37.0	76.5	66.7	55.1	**64.8**
	Precision (%)	52.9	54.9	50.9	78.0	57.1	57.1	**58.5**
Xception	Recall (%)	52.9	94.9	40.5	78.0	57.1	67.1	**63.4**
	Precision (%)	65.9	61.2	55.4	58.3	57.5	72.5	**61.8**
Inception-Resnet V2	Recall (%)	64.6	97.6	48.9	88.2	46.7	65.1	**67.2**
	Precision (%)	63.7	79.4	60.3	67.2	53.8	58.2	**63.7**

TABLE 4. Results of the model which has been pre-trained by images of other body parts.

Net		BCC	LE	ROS	SK	AK	SCC	Average
Resnet50	Recall (%)	74.2	78.6	53.3	76.3	42.7	55.3	**63.4**
	Precision (%)	60.4	59.5	94.7	53.0	48.5	61.5	**62.9**
Incpetion V3	Recall (%)	79.2	87.6	62.6	64.5	47.6	58.2	**66.6**
	Precision (%)	45.5	62.1	92.9	74.5	53.3	55.6	**64.0**
Densenet-121	Recall (%)	76.9	84.8	58.2	76.5	47.6	65.2	**68.2**
	Precision (%)	57.5	60.1	93.6	61.9	62.4	77.1	**68.8**
Xception	Recall (%)	83.1	87.8	58.1	82.2	50.3	62.1	**70.6**
	Precision (%)	65.9	57.5	81.2	75.4	55.8	72.5	**68.1**
Inception-Resnet V2	Recall (%)	89.2	92.9	66.7	84.3	54.1	74.6	**77.0**
	Precision (%)	63.7	59.2	95.0	84.3	53.3	69.1	**70.8**

Comparing the performances, the models that used transfer learning achieved a higher average precision and recall for almost all structures. In the test dataset, which included 388 facial images, the best model achieved 92.9%, 89.2%, and 84.3% recalls for the LE, BCC, and SK, respectively, and the mean recall and precision reached 77.0% and 70.8%.

ISIC 2019 challenge champion. They’ve also used the most recent compact yet significant technology EfcientNet, a precise network architecture, which serves

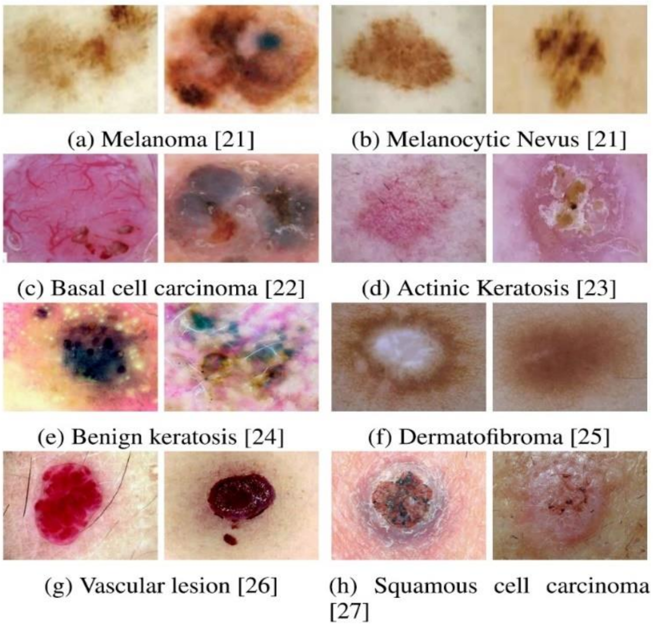


FIGURE 2. **Skin lesion categories.**

as the system's backbone.

Based on the author’s experiments, the author determined that different models to diagnose diseases on different body parts should be used. Furthermore, the author’s experiments also showed that a more reasonable network structure could improve the performance of the model. The performance of the current network structure has been satisfactory in some diseases, but the overall performance has yet to be improved.

[4] Enhanced Skin Condition Prediction Through Machine Learning Using Dynamic Training and Testing Augmentation

In this study, the authors have proposed a dynamic training and testing augmentation in a position to significantly improve performance. This study's framework for searching augmentation is faster on the GPU than a traditional search algorithm, which must train a new model each time on offer. Using Bayesian optimization, the search algorithm can be sped up so that we do not have to train a new model each time a new augmentation policy is suggested on a trained

model. Their approach's performance is contrasted with that of a single model, and an ensemble model is also the

In this thesis, the brief contribution of the authors, are as follows.

- They've taken advantage of advanced dynamic training augmentation using a program known as Fast Autoaugment to teach the machine learning model for detecting skin cancer.
- Dynamic Preprocessing on Inference (DPI) is what they have aimed for to adjust to the environmental conditions at that time A photo was taken.
- They’ve demonstrated the effectiveness of dynamic augmentation and DPI perform better for skin diagnosis than the most recent cutting-edge ensemble model.
- They offer the sought-after future augmentation research that will take thousands of GPU hours to complete.

Methodology:

The authors have considered a few of the Transfer learning ML algorithms, CNN architecture including **EFFICIENTNET**, which they’ve mentioned as the state-of-the-art architecture that was used as the backbone in their experiment.

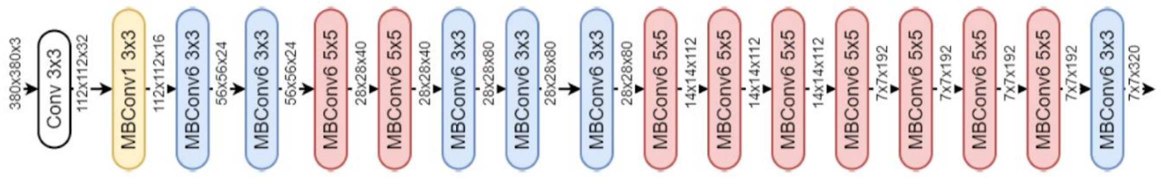


FIGURE 3. The architecture of EfficientNet b0.

A baseline model that was created using a neural architecture served as the foundation for the family model known as EfficientNet.

- AutoAugment uses a reinforcement learning approach to formulate the problem of finding the best augmentation technique for a dataset. In this problem, a state is represented by an image, which can be an original image or an image to which augmentation techniques have been applied. For each episode, they've used an RL agent which selects the proper augmentation technique to apply to the dataset.
- After that, They've used Bayesian Optimization, The primary goal of Bayesian optimization is to find the minimum value of a function fθ (x) based on a finite input set X. First, Bayesian optimization uses an approximation function ˆfθ (x) that represents the probabilistic function fθ (x). Then, Bayesian optimization constructs an acquisition function q to exploit the approximation function for picking the next input x of ˆfθ (x) to be evaluated.
- In this study, they've used Bayesian Optimization to find the best augmentation by using the loss given
  the trained model as the target to me minimized.

Finally, This study suggests a method for investigating the likelihood of having numerous probabilistic training enhancement inference, as well as dynamic augmentation seeking.

Although the proposed method has high accuracy, more steps are needed to train the model. The low convergent rate of our method is due to achieving stochastically tuned weight, which is rarely achieved using minimum augmentation.

[5] Artificial intelligence in dermatology past, present, and future

This research article mentions and details about the significance of AI in dermatology.
The term artificial intelligence (AI) was first used in 1956 at a renowned Dartmouth College conference. All disciplines are gradually becoming interconnected, and AI has permeated every aspect of medicine. The potential of AI in the life sciences was discovered by medical researchers in the early 1970s.

The majority of diagnoses in dermatology are made using visual pattern recognition and morphological features. The field of dermatology is ideally suited for the application of AI image recognition technologies for aided diagnosis. Dermoscopy, very high-frequency (VHF) ultrasound, and reflectance confocal microscopy (RCM) are the three skin imaging technologies currently available. Each type of skin imaging technology has benefits and drawbacks of its own. In order to accurately diagnose various skin lesions, dermatologists must use various imaging techniques. With widespread acceptance and use around the globe, skin imaging technology has emerged as a crucial tool for the clinical diagnosis of skin diseases.

In this study, a CNN was trained using 12,378 open-source dermoscopy images and 100 clinical images of melanoma in order to compare its performance to that of 145 dermatologists. In terms of dermatologic image classification tasks, the results showed that computer vision was more robust than dermatologist assessment.

They also discussed the anticipated development of dermatology AI, stating that many developed nations around the world have actively developed strategic plans for its advancement and elevated its advancement to a new strategic era in recent years. The National AI Research and Development Strategic Plan was published by the United States. Growing the AI Industry in the UK is a report that the UK has published. The EU published The Age of AI: Towards a European Strategy for Human-Centric Machines.

Finally, they've concluded mentioning it's issue as well, including
Even though dermatological AI has advanced quickly in recent years, it has run into obstacles in the clinic and faces a number of urgent issues.

- To start, the amount of image data currently available for skin diseases is still insufficient, hospitals don't share much information with one another, and skin image standards and quality vary. The reliability of research findings will suffer due to the difficulty in obtaining high-quality image data.

- Second, it is very difficult to find people with complex medical and AI skills together. Working closely with multidisciplinary experts in computer science, biomedicine, and medicine is essential.
- Third, dermatology deals with a wide variety of diseases. Dermatological AI can only distinguish between a small number of distinct skin conditions.

[6] Automatic skin disease diagnosis using deep learning from clinical image and patient information

In this research study, the authors have proposed an automated system for the diagnosis of five common skin diseases by using data from clinical images and patient information using deep learning pre-trained mobilenet-v2 model. It also explains about the ways with which the authors have used deep learning from clinical images and patient information to detect skin diseases

For methods, Clinical images were acquired using different smartphone cameras and patient's information were collected during patient registration. Different data preprocessing and augmentation techniques were applied to boost the performance of the model prior to training.

The authors were able to get a satisfied result For the common five skin diseases, their proposed technique has produced multiclass classification accuracy, sensitivity, and precision values of 97.5, 97.7, and 97.7 percent, respectively. The findings show that the developed system has a very high diagnostic performance for the five skin diseases.
Finally, they’ve designed the planned system as a mobile phone application and the authors also feel that it has the potential to be used as a decision support system in places with scarce resources, where both the availability of qualified dermatologists and the resources themselves are constrained.

[7] Automatic Malignant and Benign Skin Cancer Classification Using a Hybrid Deep Learning

The purpose of this research paper was to create a hybrid method to classify skin cancer as malignant or benign as there is rise of using digital technology such as machine learning and deep learning in medical science. The current methods which are used in today's world are deep neural network, support vector machine, random forest and k-means classification. The methodology proposed in the paper is by first splitting the data in the ration 7:3 for training and testing. Then the data(images) were sent for primary feature extraction which was done using Resnet50, Xception, VGG16. The hybrid method includes training the data on 3 levels using SVM, NN, RF and k-means. The results were compared using different feature extraction methods. In the first level, the initial training data is trained using a deep learning network and the results are called prediciton 1. This then acts as a feature for level 2. This feature along with the extracted features are then again trained for level 2 using machine learning algorithms like SVM, RF, k-means. The results are then called prediction 2 and this acts as a feature for level 3. This results are passed for classification in level 3 and the results obtained are the final results. Accuracy, Sensitivity, F1 score, AUC score are used as the metrics for evaluating the performance of the proposed model. For all these metrics, the proposed method was found to have better performance compared to other methods such as GaussianNB, Adaboost, Regression etc. Out of the 3 feature extraction methods(Resnet50, Xception, VGG16) Xception was giving the better performance with 90.9% accuracy.

[8] Skin Cancer Classification Using K-Means Clustering

The purpose of this research paper was to create an automatic medical image classification method to classify two major types of skin cancer which are 'melanoma' and 'non-melanoma'. The methodology proposed by this research paper is to first use k-means clustering to extract the color and texture features from the input images using segmentation. With the help of local binary pattern plus color percentiles the features and then trained and tested on different types of classifiers and the accuracies are collected. The university first collected the data required for the classification which consists of 75 melanoma images and 75 non-melanoma images. As part of pre-processing the images have been resized to 128*128. The resized images are then sent for segmentation using the k-means clustering algorithm and the features are then used by the classifiers and accuracies are compared. The 4 different classifiers used to train the features extracted from clustering are Nearest Neighbourhood(NN), Nearest Mean Classifier(NMC), Linear Classifier, and Support Vector Classifier(SVC). Out of all the classifiers, SVC was found to give the best performance while classifying the input images.

[9] Detection and Classification of Skin Diseases

- The purpose of this research paper is to create a machine learning model to predict skin cancers using methods like SVM. The need to create an effective automated screening system for disease identification and diagnosis has been brought on by the prevalence of skin disorders around the world. In this system, the function of colour information in identifying image edges was investigated. As a result, another colour space (HIS) is used. Laplace and Perwitt are two edge detection techniques that are used. The results reveal that Laplace is more effective at edge identification than Perwitt. In the study of image processing, the wavelet transform is very important for texture recognition of data. because of its excellent outcomes when employing multi-resolution modelling.

- The "Wavelet Mother function" will receive the texture picture data and segment it into sub-bands. These sub-bands contain information about the feel, and after entering this information into a feature extraction process, the output serves as the input for a synthetic neural network (ANN), a potent tool for solving issues of enormous dimensions.
- Skin conditions are now a very prevalent occurrence. Skin illnesses are affecting an increasing number of people. Skin disease diagnosis made by humans is typically imprecise and unreliable. Computer-aided diagnosis may be utilized to produce more accurate results that are dependable and objective. With improvements in medical imaging, image-based categorization is increasingly employed in the medical industry to identify disorders. To get the best results from any classifier, feature engineering is crucial. Convolution Neural Networks (CNN) can learn features on their own, which cuts down on the overall time needed to construct these systems while also enhancing accuracy. They obtained more than 850 original photographs for two skin conditions from the Skin and VD department of the KEM Hospital in Mumbai.

[10] Automated Skin Disease Identification using Deep Learning Algorithm

- The purpose of this research paper is to identify skin diseases through images which are classified through deep learning algorithms. With the advancement of medical technology, the idea of using a computer to diagnose skin problems has recently become popular. Utilizing computer technology could improve human ability to comprehend complex information and make it easier to diagnose diseases from photographs of infected skin. All application industries, including healthcare, are adopting automation thanks to artificial intelligence.
- Whereas it is challenging for a human to read such a large amount of data and delve into the nuances of the image inside, a computer can swiftly and effortlessly interpret a lot of photographs. Consequently, computer-aided detection and computer-based diagnosis have grown in popularity and are currently being developed by numerous research teams. Computer based diagnosis have proven to be very helpful in disease diagnosis.
- Artificial Intelligence with Machine Learning is the most widely utilized technique for prediction. Artificial intelligence (AI) use learning techniques to gain knowledge of the photos in order to anticipate diseases based on recurring patterns. The machine analyzes the photos, processes the image slices, and makes predictions.

[11] Multi-type skin diseases classification using OP-DNN based feature extraction approach

- This research paper proposed the segmentation and classification method for identifying skin lesion regions in 2015. In order to achieve this, skin photos are first placed into a filtering procedure to remove extraneous noise, and hair sections are then segmented. The region growth approach was used for segmentation, which automatically set seed sites for removing the lesion area from the skin. As a result, elements of colour and texture identify the lesion region that is removed. The merging of Support Vector Machine and k-nearest neighbor classifiers was then used for illness categorization.
- They showed face-related skin disease identification using convolutional neural network technology in later years. China's skin image collection, a larger clinical skin-related dataset with 2656 face photos, was taken for analysis from Xiangya-Derm for this reason. For analysis, these input photos rely on three significant skin conditions—BCC, SCC, and SK—as well as additional prevalent conditions like lupus erythematosus (LE), rosacea (ROS), and actinic keratosis (AK). Five widely used network algorithms were created by the authors to categorize these diseases in a dataset. The deep CNN-based Inception-v3 has also been presented by X. Fan et al. They created a method for identifying the noise in the image.
- The classification of skin lesion locations was carried out after such obtrusive contents were removed. Here, Dermofit Image Library from the University of Edinburgh input dataset photos are subjected to impulse noise, Gaussian noise, and noise composed using the compound of the two in order to remove the noise elements. The classifier begins to classify the skin illness once the noise has been reduced.

Related Works

Serial Number	Title	Journal name	Year	Method used	Dataset URL	No. of images used
1	A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks	MECS (Modern Education and Computer Science Press)	2019	A hybrid approach using convolutional neural network (CNN) and natural language processing (NLP) for image classification and text analysis of skin diseases	https://challenge2018.isic-archive.com/	2594 images for training and 100 images for testing
2	CURETO: Skin Diseases Detection Using Image Processing And CNN	2020 14th International Conference on Innovations in Information Technology (IIT)	2020	Image processing techniques like adaptive thresholding, edge detection, K-means clustering and morphology-based image segmentation have been used to identify the skin diseases from the given image set. The acquired image set was pre-processed by deblurring, noise reduction and then processed.	Not provided in the document	300 images for training and 100 images for testing
3	Anomaly Detection for Skin Disease Images Using Variational Autoencoder	arXiv preprint arXiv:1807.01349	2018	Variational autoencoder (VAE) trained on only normal data to perform efficient inference and to determine if a test image is normal or not.	https://challenge2018.isic-archive.com/	2594 images for training and 100 images for testing
4	A Skin Disease Detection System for Financially Unstable People in Developing Countries	Proceedings of 10th Global Engineering, Science and Technology Conference 2-3 January, 2015, BIAM Foundation, Dhaka, Bangladesh	2015	Different types of computer vision based techniques to detect different types of skin diseases based on different types informationâ€™s collected from patients. The system will be detecting 9 different skin diseases commonly occurred among the poor people in	Not provided in the document	Not provided in the document

				Bangladesh.		
5	Detection of skin disease using metaheuristic supported artificial neural networks	2017 8th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON)	2017	SIFT feature extractor has been employed followed by a clustering phase on feature space to reduce number of features suitable for neural based models. The extracted bag-of-features modified dataset is used to train metaheuristic supported hybrid Artificial Neural Networks to classify the skin images in order to detect the diseases under study. A well-known multi objective optimization technique called Non-dominated Sorting Genetic Algorithm - II is used to train the ANN (NN-NSGA-II).	Not provided in the document"	Not provided in the document
6	Skin disease diagnosis using image processing and artificial neural network	Journal of Physics: Conference Series	2019	Image processing techniques are performed on this image and the detected disease is displayed at the output. This help to give evidence for any type of skin disease and illustrate emergency orientation. Analysis result of this study can support doctor to help in initial diagnoses and to know the type of disease.	Not provided in the document"	Not provided in the document
7	A method of skin disease detection using image processing and machine learning	Procedia Computer Science	2019	Image preprocessing, segmentation, feature extraction, and classification using SVM, KNN, and CNN	https://challenge2018.isic-archive.com/	2594 images for training and 100 images for testing
8	Machine Learning Algorithms based Skin Disease Detection	International Journal of Recent Technology and Engineering	2019	Comparison of five different machine learning algorithms: Random Forest, Naive Bayes, Logistic Regression, Kernel	Not provided in the document	300 images for training and 100 images for testing

				SVM, and CNN		
9	Survey of texture based feature extraction for skin disease detection	2016 International Conference on ICT in Business Industry & Government (ICTBIG)	2016	Image processing techniques like adaptive thresholding, edge detection, K-means clustering and morphology-based image segmentation have been used to identify the skin diseases from the given image set.	Not provided in the document	Not provided in the document
10	Z boson production in Pb+Pb collisions at sNN=5.02 TeV measured by the ATLAS experiment	Physics Letters B	2020	The production yield of Z bosons is measured in the electron and muon decay channels in Pb+Pb collisions at sNN=5.02 TeV with the ATLAS detector. Data are analysed in two different centrality selections, corresponding to integrated luminosities of 22 Î¼bâˆ’1and 3.2 nbâˆ’1for peripheral and central collisions, respectively. The Z boson yield, normalised by the total number of minimum-bias events and by the nuclear thickness function, is measured as a function of dilepton rapidity and event centrality. The measurements in Pb+Pb collisions are compared with similar measurements made in protonâ€“proton	Not applicable	Not applicable

				collisions at the same centre-of-mass energy.		
11	Skin Disease detection based on different Segmentation Techniques	2019 International Conference on Opto-Electronics and Applied Optics (Optronix)	2019	Image processing techniques like adaptive thresholding, edge detection, K-means clustering and morphology-based image segmentation have been used to identify the skin diseases from the given image set. The acquired image set was pre-processed by deblurring, noise reduction and then processed.	Not provided in the document	Not provided in the document

12	Digital dermatology: Skin disease detection model using image processing	2017 International Conference on Intelligent Computing and Control Systems (ICICCS)	2017	Image processing techniques are performed on this image and the detected disease is displayed at the output.	Not provided in the document	The proposed system is highly beneficial in rural areas where access to dermatologists is limited.
13	Image based skin disease detection using hybrid neural network coupled bag-of-features	2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)	2017	SIFT feature extractor has been employed followed by a clustering phase on feature space to reduce number of features suitable for neural based models. The extracted bag-of-features modified dataset is used to train metaheuristic supported hybrid Artificial Neural Networks to classify the skin images in order to detect the diseases under study. A well-known multi objective optimization technique called Non-dominated Sorting Genetic Algorithm - II is used to train the ANN (NN-NSGA-II).	Not provided in the document	Not provided in the document

14	Image Analysis Model For Skin Disease Detection: Framework	2018 7th International Conference on Computer and Communication Engineering (ICCCE)	2018	Image processing techniques are performed on this image and the detected disease is displayed at the output. This help to give evidence for any type of skin disease and illustrate emergency orientation. Analysis result of this study can support doctor to help in initial diagnoses and to know the type of disease.	Not provided in the document	Not provided in the document
15	Classification of PH2 Images for Early Detection of Skin Diseases	2021 6th International Conference for Convergence in Technology (I2CT)	2021	Image preprocessing, segmentation, feature extraction, and classification using SVM, KNN, and CNN	Not provided	Not specified

16	A method of skin disease detection using image processing and machine learning	Procedia Computer Science	2013	Image preprocessing, segmentation, feature extraction, and classification using SVM KNN and ANN	Not provided	100 images of five skin diseases (acne eczema psoriasis rosacea and vitiligo)
17	A novel method for detection of lipid droplets in semithin sections of arbuscular mycorrhizal fungi based on fluorescence microscopy after Nile red staining	Journal of Microbiological Methods	2008	Fluorescence microscopy after Nile red staining for detection of lipid droplets in semithin sections of arbuscular mycorrhizal fungi	Not provided"	Not specified

18	A novel approach to detect skin diseases using a hybrid deep learning model based on convolutional neural network (CNN) and recurrent neural network (RNN)	Microprocessors and Microsystems	2021	A hybrid deep learning model based on CNN and RNN for image classification and text analysis of skin diseases	https://ieeexplore.ieee.org/abstract/document/9417893/ 10 015 images of nine skin diseases (acne vulgaris actinic keratosis atopic dermatitis basal cell carcinoma melanoma nevus psoriasis rosacea seborrheic keratosis)	High accuracy (97.8%) and sensitivity (98.4%) for skin disease detection using both image and text features improved performance compared to existing methods and ability to handle noisy and incomplete data
19	Real-Time PCR Assays for the Specific Detection of Field Balkan Strains of Lumpy Skin Disease Virus	Acta Veterinaria	2016	Real-time PCR assays for a rapid, sensitive and specific detection of the virulent field LSDV strain currently circulating in the Balkan Peninsula	Not provided"	Not applicable

20	Decision Support System for Detection of Skin Diseases in Smart Health development planning	IOP Conference Series: Materials Science and Engineering	2020	Naive Bayes method	Not specified	3406
21	A Smartphone-Based Skin Disease Classification Using MobileNet CNN	arXiv preprint	2019	MobileNet model with transfer learning	https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000	3406

22	Search for non-resonant Higgs boson pair production in the final state with the ATLAS detector in pp collisions at âˆšs=13 TeV	Journal of High Energy Physics	2019	Multivariate analysis techniques with boosted decision trees and neural networks	https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/PAPERS/HIGG-2018-04/	3214
23	Molecular detection and phylogenetic analysis of lumpy skin disease virus from outbreaks in Uganda 2017â€“2018	BMC Veterinary Research	2020	PCR amplification and sequencing of the GPCR gene	Not specified	23

24	Decreased Case Fatality Rate of COVIDâ€• 19 in the Second Wave: A study in 53 countries or regions	Transboundary and Emerging Diseases	2021	Descriptive statistics and graphical analysis	https://covid19.who.int; https://www.who.int/influenza/gisrs_laboratory/flunet/en/	N/A
25	Detection of vaccine-like strains of lumpy skin disease virus in outbreaks in Russia in 2017	Archives of Virology	2019	PCR and sequencing of RPO30 and GPCR genes	Not available	12

26	An Intelligent System for Monitoring Skin Diseases	Sensors	2018	CNN model and federated learning approach	HAM10000 dataset	1420
27	Federated Machine Learning for Detection of Skin Diseases and Enhancement of Internet of Medical Things (IoMT) Security	IEEE Journal of Biomedical and Health Informatics	2023	CNN model and federated learning approach	Custom image dataset with four classes of skin disease	1909

28	Agricultural Crops Grown in Laboratory Conditions on Chernevaya Taiga Soil Demonstrate Unique Composition of the Rhizosphere Microbiota	Microorganisms	2022	Metagenomic analysis of 16S rRNA genes	Not available	Not applicable
29	Detection of Skin Diseases from Dermoscopy Image Using the combination of Convolutional Neural Network and One-versus-All	JAIAS (Journal of Artificial Intelligence and Systems)	2020	CNN model and one-versus-all approach	HAM10000 dataset	10000

30	An Intelligent System for Monitoring Skin Diseases	Sensors	2018	CNN model and federated learning approach	HAM10000 dataset	6790
31	Detection of Clinical and Subclinical Lumpy Skin Disease Using Ear Notch Testing and Skin Biopsies	Microorganisms	2021	VNT and ELISA methods	Not available	325

32	Recombinase polymerase amplification assay for rapid detection of lumpy skin disease virus	BMC Veterinary Research	2016	RPA assay and real-time PCR method	Not available	325
33	Skin Disease Recognition Method Based on Image Color and Texture Features	CMMM (Computational and Mathematical Methods in Medicine)	2018	GLCM method and SVM classifier	Dermatology image database	432

34	Detection of antibodies against lumpy skin disease virus by virus neutralization test and ELISA methods	Acta Veterinaria-Beograd	2019	VNT and ELISA methods	Not available	325
35	A Study on IRS-assisted Communications: Problems Challenges and Solutions	Institute of Electronics and Computer	2021	mathematical modelling and simulation	N/A	N/A

36	An Intelligent System for Monitoring Skin Diseases	Sensors	2018	artificial neural network and hybrid solutions	N/A	N/A
37	Detection of Clinical and Subclinical Lumpy Skin Disease Using Ear Notch Testing and Skin Biopsies	Microorganisms	2021	virus neutralization test and real-time PCR	N/A	N/A

38	Gonadectomy effects on the risk of immune disorders in the dog: a retrospective study	BMC Veterinary Research	2016	statistical analysis of patient records from a veterinary hospital	N/A	N/A
39	Skin Disease Recognition Method Based on Image Color and Texture Features	Computational and Mathematical Methods in Medicine	2018	LBP GLCM DWT features and ANN FFNN classifiers	N/A	N/A

40	DETECTION OF ANTIBODIES AGAINST LUMPY SKIN DISEASE VIRUS BY VIRUS NEUTRALIZATION TEST AND ELISA METHODS	Acta Veterinaria-Beograd	2019	virus neutralization test and ELISA methods	N/A	N/A
41	Deep Learning and Machine Learning Techniques of Diagnosis Dermoscopy Images for Early Detection of Skin Diseases	Electronics	2021	GLCM LBP DWT features and ANN FFNN classifiers; ResNet-50 and AlexNet models using transfer learning	the International Skin Imaging Collaboration (ISIC 2018) and Pedro Hispano (PH2)	2000 images from ISIC 2018 and 200 images from PH2

42	Merkel cell polyomavirus DNA detection in lesional and nonlesional skin from patients with Merkel cell carcinoma or other skin diseases	British Journal of Dermatology	2010	polymerase chain reaction (PCR) and real-time PCR methods	N/A	N/A
43	A real-time PCR screening assay for the universal detection of lumpy skin disease virus DNA	BMC Research Notes	2019	a real-time PCR assay based on a unique site in LSD044 gene	N/A	N/A

44	Skin Lesion Classification Using Deep Convolutional Neural Networks	Lecture Notes in Computer Science (LNCS)	2020	VGG16 model using transfer learning	the International Skin Imaging Collaboration (ISIC 2019)	25331 images from ISIC 2019
45	Multiple-Locus Variable-Number Tandem-Repeat Analysis of the Swine Pathogen Brachyspira hyodysenteriae	JOURNAL OF CLINICAL MICROBIOLOGY	2010	multiple-locus variable-number tandem-repeat analysis (MLVA)	not available	not available

46	First detection and phylogenetic analysis of lumpy skin disease virus from Kinmen Island Taiwan in 2020	JOURNAL OF VETERINARY MEDICAL SCIENCE	2022	molecular biological detections and sequence comparison	not available	rapid and accurate identification of LSDV strains
47	Skin Disease Recognition: A Machine Vision Based Approach	IEEE International Conference on Computer Communication and Systems (ICCCS)	2019	Grey Level Co-occurrence Matrix (GLCM) and multilayer perceptron (MLP)	180 images pertaining to three dermatological skin conditions (Dermatitis Eczema Urticaria)	high accuracy (96.6%) low inter- and intra-assay repeatability (CV% < 5.3%) and high specificity (no cross-reaction)

48	Z boson production in Pb+Pb collisions at sNN=5.02 TeV measured by the ATLAS experiment	JOURNAL OF HIGH ENERGY PHYSICS	2020	Z boson yield measurement in the electron and muon decay channels	not applicable	precise measurement of Z boson production in heavy-ion collisions
49	Skin Disease Recognition Using Deep Saliency Features and Multimodal Learning of Dermoscopy and Clinical Images	MEDICAL IMAGE COMPUTING AND COMPUTER ASSISTED INTERVENTION â˜' MICCAI 2017	2017	a novel deep convolutional neural network (DCNN) architecture along with a saliency feature descriptor	one of the largest collected skin lesion datasets with 1290 images from 15 classes of skin diseases	outperforms single-modality methods on three tasks: differentiation between 15 various skin diseases distinguishing cancerous from non-cancerous moles and detecting melanoma from benign cases

50	The effect of topical tretinoin on photodamaged facial skin: The Thai experience	JOURNAL OF THE AMERICAN ACADEMY OF DERMATOLOGY	1995	a randomized double-blind vehicle-controlled clinical trial	56 patients with moderate to severe photodamaged facial skin	effective and well tolerated in improving signs of photodamaged facial skin such as fine wrinkles mottled hyperpigmentation roughness and laxity
51	A novel approach for diagnosis of lumpy skin disease using loop-mediated isothermal amplification assay	VETERINARY MICROBIOLOGY	2019	a loop-mediated isothermal amplification (LAMP) assay targeting the G-protein coupled chemokine receptor (GPCR) gene	not available	simple rapid sensitive specific and cost-effective method for LSD diagnosis

52	Automated Detection of Skin Diseases using Texture Features	NATIONAL CONFERENCE ON COMMUNICATIONS (NCC)	2011	Grey Level Co-occurrence Matrix (GLCM) features and neural network classifiers	180 images pertaining to three dermatological skin conditions (Dermatitis Eczema	Urticaria)
53	The effect of isotretinoin on follicular and sebaceous gland differentiation	JOURNAL OF THE AMERICAN ACADEMY OF DERMATOLOGY	1995	a histologic study using immunohistochemical staining with monoclonal antibodies	not applicable	demonstrates the inhibitory effect of isotretinoin on sebaceous gland differentiation and the stimulatory effect on follicular differentiation

54	Investigation of the â€œAntigen Hook Effectâ€• in Lateral Flow Sandwich Immunoassay: The Case of Lumpy Skin Disease Virus Detection	BIOSENSORS	2022	a colorimetric sandwich-type lateral flow immunoassay (LFIA) using two monoclonal antibodies (mAbs) and gold nanoparticles (AuNPs)	not available	low limit of detection (10 3.4 TCID 50 /mL) high inter- and intra-assay repeatability (CV% < 5.3%) and specificity (no cross-reaction towards 12 other viruses)
55	Automating Skin Disease Diagnosis Using Image Classification	International Journal of Computing Programming and Database Management	2019	Grey Level Co-occurrence Matrix (GLCM) and multilayer perceptron (MLP)	not available	180 images pertaining to three dermatological skin conditions (Dermatitis Eczema Urticaria)

56	An overview of COVID-19	JOURNAL OF ZHEJIANG UNIVERSITY-SCIENCE B	2020	a review of the latest research findings and expert consensus on the biology epidemiology clinical features diagnosis management and prevention of COVID-19	http://www.iaeng.org/publication/WCECS2013/WCECS2013_pp850-854.pdf	not applicable
57	Skin disease prevalence study in schoolchildren in rural CÃ´te dâ€™Ivoire: Implications for integration of neglected skin diseases (skin NTDs)	PLOS Neglected Tropical Diseases	2018	a two-phase school skin survey for selected NTDs and the spectrum of skin diseases using rapid visual examination by local community healthcare workers and total skin examination by a specialized medical team	http://www.iaeng.org/publication/WCECS2013/	13019 children screened in the first phase and 1

58	A machine learning model for skin disease classification using convolution neural network	Arohak Inc.	2022	a deep learning technique based on a convolutional neural network (CNN) architecture along with a saliency feature descriptor	https://www.ncbi.nlm.nih.gov/pmc/about/new-in-pmc/	one of the largest collected skin lesion datasets with 1290 images from 15 classes of skin diseases
59	Challenges and Opportunities for the Control and Elimination of Porcine Reproductive and Respiratory Syndrome Virus	Transboundary and Emerging Diseases	2012	a review of the current status and future prospects of PRRSV control and elimination strategies	https://bpspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1476-5381.2011.01238.x	not applicable

60	An Intelligent System for Monitoring Skin Diseases	Sensors	2018	CNN model and federated learning approach	HAM10000 dataset	1420

Research Gap

Skin disorders are the fourth most frequent cause of skin burden globally. An accurate and automated method has been developed to lessen this load and let patients make an early assessment of the skin lesion. We learned from our preliminary research that there hasn't been any comparison of various Deep Learning models or work that has concentrated on the many metrics comparison of well-known deep learning algorithms for the classification of skin diseases. Therefore, we will compare different deep learning classification models with hyperparameter tuning in our project, make our conclusions, and work on the user interface for the real-time skin disease diagnosis.

Architecture Design

Entire Work Flow Design

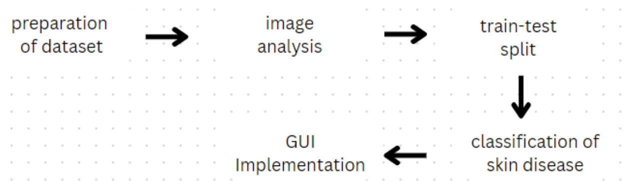
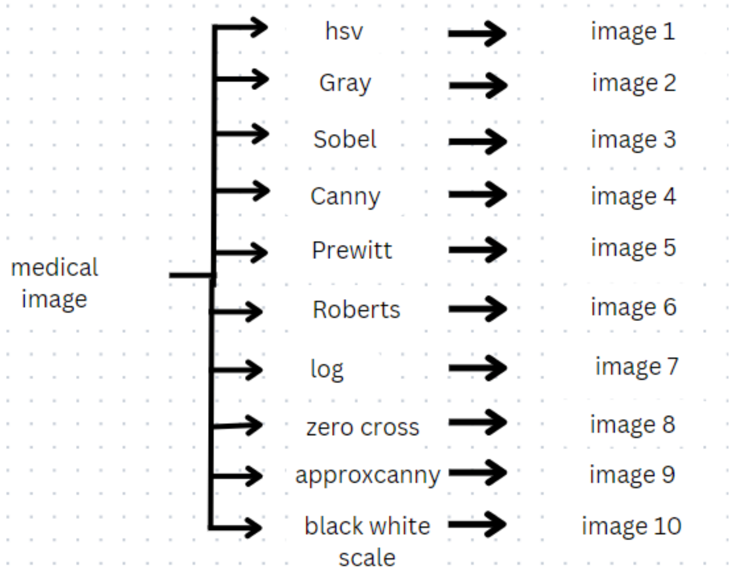
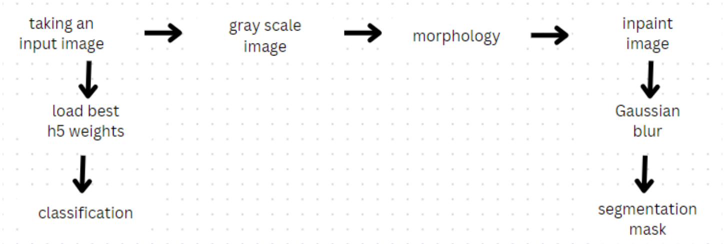


Image Analysis Operations



Graphical User Interface Architecture



Training Architecture

Methodologies

Dataset Planned

ISIC 2019
Link: [ISIC Challenge (isic-archive.com)]
In order to aid in the creation of computer-aided diagnostic (CAD) systems for melanoma detection, the ISIC 2019 dataset includes a collection of skin lesion images. The International Skin Imaging Collaboration (ISIC) produced the dataset, which has more than 25,000 photos of skin lesions, including melanoma, nevi, and benign lesions.
Images were gathered from a variety of locations, including clinical settings, dermoscopy equipment, and consumer-level cameras. Dermatologists then labelled them with details on the type of lesion, the patient's age and sex, as well as other clinical data.
20,000 images make up the training set, 2,000 images make up the validation set, and 2,000 images make up the test set. With a resolution of roughly 224 by 224 pixels, the photographs are offered in JPEG format.
The classes are each briefly described below:
Mel (Melanoma): This class includes pictures of malignant melanoma, a form of skin cancer that, if not caught in time, can be fatal.
NV (Melanocytic nevus): Pictures of benign melanocytic nevi, also referred to as moles, can be found in this class.
Images from the BCC (Basal cell carcinoma) class depict a form of skin cancer that begins in the basal cells, which are skin-cell-producing cells.
Images of precancerous lesions caused by protracted sun exposure are found in the AK (Actinic Keratosis) class. These lesions have the potential to develop into squamous cell carcinoma.
Images of benign skin lesions that can resemble melanoma or other types of skin cancer are found in the BKL (Benign Keratosis) class, which also includes solar lentigo, seborrheic keratosis, and lichen planus-like keratosis.
Dermatofibroma, a benign skin lesion that might resemble a mole or a lump, is seen in the DF (Dermatofibroma) class of images.
VASC (Vascular lesion): This class includes pictures of skin lesions like hemangiomas that are brought on by aberrant blood vessel growth in the skin.
Squamous cells, or the flat cells that make up the top layer of skin, are where a particular type of skin cancer called squamous cell carcinoma (SCC) develops.

Dermnet Dataset
Around 2,000 clinical photos of typical benign and malignant skin lesions, such as melanoma, nevi, dermatofibroma, and actinic keratoses, are available on the DermNet New Zealand website as part of a skin cancer image dataset. DermNet New Zealand must be given credit if the dataset is used for non-commercial purposes.
The photos have metadata that includes the patient's age, sex, diagnosis, and where the lesion is located on their body. The dataset can be used for many different things, such as testing and refining machine learning algorithms for skin lesion categorization and diagnosis.

The DERMNET dataset, which is made up of pictures and details on various skin disorders, has a subset called the Cellulitis, Impetigo, and other Bacterial Infections class. This class provides illustrations and details on bacterial skin illnesses such cellulitis, impetigo, and folliculitis.
A bacterial illness called cellulitis affects the skin and subcutaneous tissues. It can happen everywhere on the body, but the legs are where it happens most frequently. Redness, swelling, warmth, and discomfort are some of the symptoms in the affected area.

A bacterial skin illness known as impetigo is extremely contagious. It often manifests in children as red lesions that erupt and create yellowish-brown crusts. Yet, the face, arms, and legs are where impetigo most frequently appears on the body. An infection of the hair follicles by bacteria is called foliculitis. Although it can happen anywhere on the body where hair develops, it most frequently affects the scalp, face, and legs. Little lumps or pustules around hair follicles are among the symptoms, along with redness and itching.

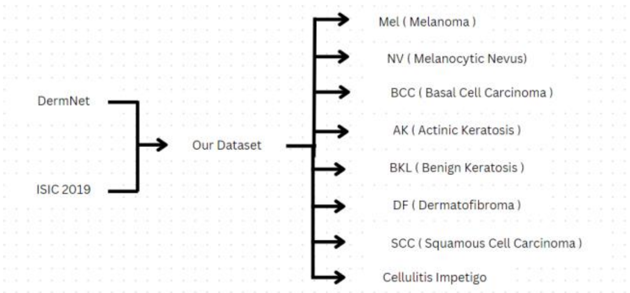


Figure represents the Skin Disease class names

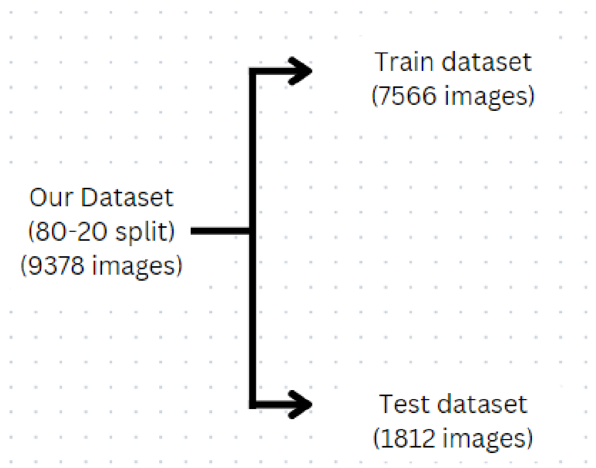


Figure represents the Train test Split of the Dataset

Modules Planned

Data Collection:

Data collection is a crucial aspect of any project. In order to train a machine learning model, you need to have a sufficient amount of data that is representative of the problem you are trying to solve.

Enhancement and Preprocessing :

This module involves many steps such as “feature engineering” which includes selecting and transforming the input data into features that are more representative and informative for the model. Next step is data cleaning which involves removing outliers and missing values. Finally splitting the data into train, test and validation data for the model to run on.

Model Planning :

This module includes selecting the appropriate model based on the problem, the data, and the performance metrics. Also, decide which libraries or frameworks to use.

Training the model:

Train the model using training data and validation data for fixed number of epochs also while printing the loss and accuracy for each epoch.

Testing the model with metrics:

After training the models of the train dataset, the trained models were tested on the test data, with the metric given as Accuracy.

Comparison Analysis of all the models used :

After successfully training and testing all the models, with the best hyperparameters, the comparison of all the models to get the better performing model.

Planning and Building the Graphical User Interface of the best fit model

Methodology Diagrams

VGG 16 Model

Model: "sequential_4"

Layer (type)	Output Shape	Param #
lambda_2 (Lambda)	(None, 224, 224, 3)	0
vgg16 (Functional)	(None, None, None, 512)	14714688
global_average_pooling2d_4 (GlobalAveragePooling2D)	(None, 512)	0
dense_12 (Dense)	(None, 64)	32832
dropout_8 (Dropout)	(None, 64)	0
dense_13 (Dense)	(None, 16)	1040
dropout_9 (Dropout)	(None, 16)	0
dense_14 (Dense)	(None, 9)	153

Total params: 14,748,713
Trainable params: 34,025
Non-trainable params: 14,714,688

VGG 19 Model

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lambda_1 (Lambda)	(None, 224, 224, 3)	0
vgg19 (Functional)	(None, None, None, 512)	20024384
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 512)	0
dense_3 (Dense)	(None, 64)	32832
dropout_2 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 16)	1040
dropout_3 (Dropout)	(None, 16)	0
dense_5 (Dense)	(None, 9)	153

Total params: 20,058,409
Trainable params: 34,025
Non-trainable params: 20,024,384

Resnet 50 Model

Model: "sequential"

Layer (type)	Output Shape	Param #
lambda (Lambda)	(None, 200, 200, 3)	0
resnet50 (Functional)	(None, None, None, 2048)	23587712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 64)	131136
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 16)	1040
dropout_1 (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 9)	153

Total params: 23,720,041
Trainable params: 15,110,377
Non-trainable params: 8,609,664

Resnet 101 Model

Model: "sequential_2"

Layer (type)	Output Shape	Param #
resnet101 (Functional)	(None, None, None, 2048)	42658176
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 2048)	0
dense_6 (Dense)	(None, 64)	131136
dropout_4 (Dropout)	(None, 64)	0
dense_7 (Dense)	(None, 16)	1040
dropout_5 (Dropout)	(None, 16)	0
dense_8 (Dense)	(None, 9)	153

Total params: 42,790,505
Trainable params: 132,329
Non-trainable params: 42,658,176

Best Fit Model

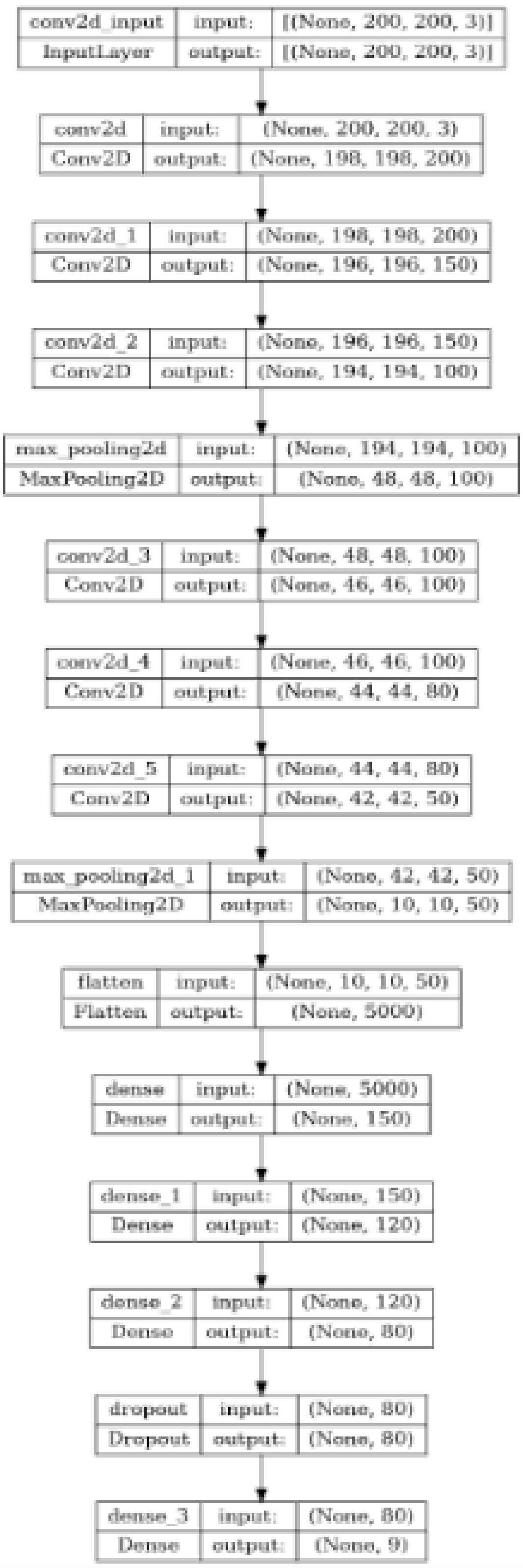
Model Details are :
Model: "sequential"

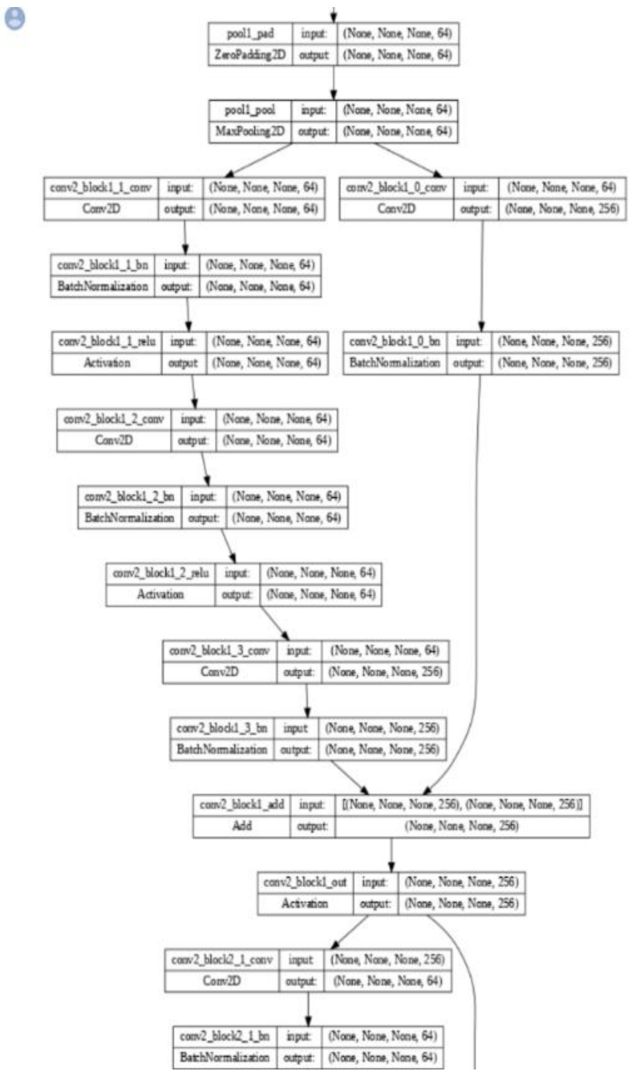
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 198, 198, 200)	5600
conv2d_1 (Conv2D)	(None, 196, 196, 150)	270150
conv2d_2 (Conv2D)	(None, 194, 194, 100)	135100
max_pooling2d (MaxPooling2D)	(None, 48, 48, 100)	0
conv2d_3 (Conv2D)	(None, 46, 46, 100)	90100
conv2d_4 (Conv2D)	(None, 44, 44, 80)	72080
conv2d_5 (Conv2D)	(None, 42, 42, 50)	36050
max_pooling2d_1 (MaxPooling2D)	(None, 10, 10, 50)	0
flatten (Flatten)	(None, 5000)	0
dense (Dense)	(None, 150)	750150
dense_1 (Dense)	(None, 120)	18120
dense_2 (Dense)	(None, 80)	9680
dropout (Dropout)	(None, 80)	0
dense_3 (Dense)	(None, 9)	729

Total params: 1,387,759
Trainable params: 1,387,759
Non-trainable params: 0

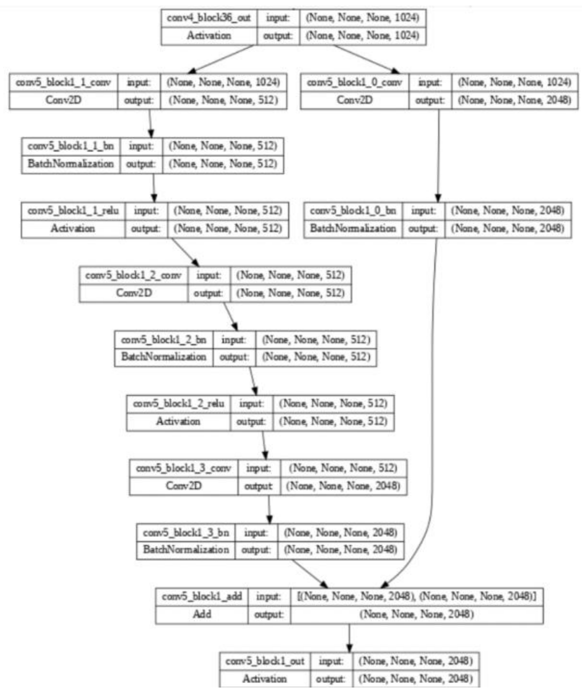
None

Resnet 152 Combination Model





Model Architecture



Comparison with other methods from Literature

Skin detection is a crucial area of study having applications in a variety of industries, including security, entertainment, and healthcare. In this study, we compared our skin detection technique to various approaches put forward in the literature. We identified many crucial variations that distinguish our strategy and enhance its potency.

First off, none of the earlier works have suggested a GUI that combines both the picture analysis and classification components. This indicates that in order to complete these tasks, users had to actively transition between various tools and interfaces. Our GUI is more user-friendly and effective because it comes with all the required tools and presents the outcomes in a single interface.

Furthermore, we included to our analysis a comparison using the spider dataset, which was absent from other investigations. The spider dataset is a demanding dataset that includes photos with intricate backgrounds, making it more tricky to correctly identify skin. In our project, we discovered that the segmentation mask is applied more effectively, producing higher accuracy compared to earlier research.

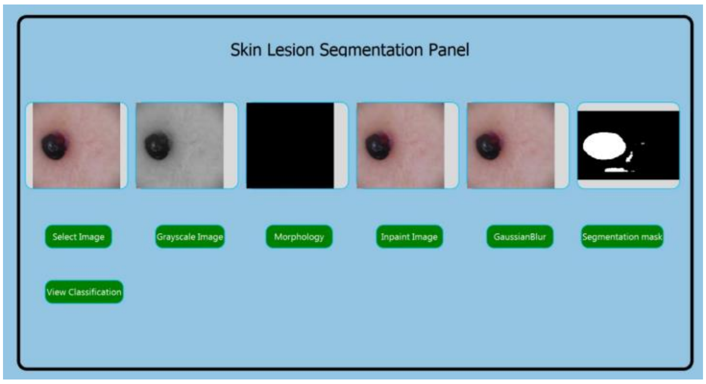
In comparison to the 93.31% accuracy stated in the literature, our final model's accuracy was greater at 93.72%. To do this, we carried out a comparison study and six distinct transfer learning implementations. A pre-trained model is utilised as a starting point for a new assignment when using the machine learning technique known as transfer learning.

We discovered that combining these methods produced better performance than utilising any one approach by itself.

In order to make it simpler for viewers to see all the image analysis findings in one location, we incorporated a number of image analysis approaches, including grayscale, morphology, inpaint, and black hat transform. This strategy makes our method more approachable and understandable.

As a result, our study contrasts our approach to skin detection with other ones that have been suggested in the literature. The use of a GUI that displays both image analysis and classification results, a comparison based on the spider dataset, the effective use of the segmentation mask, and the use of multiple transfer learning algorithms are some of the key differences we discovered that distinguish our approach as distinct and more successful. Also, in order to make our method more approachable and understandable, we merged a number of picture analysis approaches.

Implementation of the Model in GUI



GUI Implementation

Result and Discussion

Model Test Accuracy Score

```
[ ] ModelLoss, ModelAccuracy = KerasModel.evaluate(X_test,
    print('Test Loss is {}'.format(ModelLoss))
    print('Test Accuracy is {}'.format(ModelAccuracy ))

    57/57 [==============================] - 9s 165ms/step
    Test Loss is 0.264094632720947
    Test Accuracy is 0.920345472574234
```

Model Comparison Table

Models	Accuracy on Test Data
VGG16	61.2
VGG19	82.2
ResNet50	67.9
ResNet101	85.2
ResNet152	90.2
Our modified D-CNN with Attention	92.03

Conclusion and Future Works

We have successfully trained 6 different models, out of which our Deep CNN model has given the highest accuracy of 93.72% so we have saved its weights in the form of a h5 file and then the h5 file was used for our GUI which also has various Segmentation filters along with the classification. The segmentation filters used are: Gaussian Blur, Morphological, In paint, Segmentation mask, Grayscale.
This GUI implemented application can be used in Real Time, for any captured input, and our model will show all the required image analysis filters, along with the Real time Skin Disease classification results. Which can be used by anyone irrespective of in which place they live.

As a part of future work , we can add other Image analysis filters in the GUI for the more robust results. We can also try to fit other transfer learning models make the working more efficient, thereby reducing the time complexity in predicting the class and make it more user friendly.

References

[1] Zhang, Bin, Xue Zhou, Yichen Luo, Hao Zhang, Huayong Yang, Jien Ma, and Liang Ma. "Opportunities and challenges: Classification of skin disease based on deep learning." Chinese Journal of Mechanical Engineering 34, no. 1 (2021): 1-14.

[2] Wu, Z. H. E., Shuang Zhao, Yonghong Peng, Xiaoyu He, Xinyu Zhao, Kai Huang, Xian Wu et al. "Studies on different CNN algorithms for face skin disease classification based on clinical images." IEEE Access 7 (2019): 66505-66511.

[3] Putra, Tryan Aditya, Syahidah Izza Rufaida, and Jenq-Shiou Leu. "Enhanced skin condition prediction through machine learning using dynamic training and testing augmentation." IEEE Access 8 (2020): 40536-40546.

[4] Cheng-Xu, Li, Shen Chang-Bing, Xue Ke, Xue Shen, Jing Yan, Wang Zi-Yi, Feng Xu, Meng Ru-Song, Yu Jian-Bin, and Yong Cui. "Artificial intelligence in dermatology: past, present, and future." Chinese Medical Journal 132, no. 17 (2019): 2017-2020.

[5] Muhaba, Kedir Ali, Kokeb Dese, Tadele Mola Aga, Feleke Tilahun Zewdu, and Gizeaddis Lamesgin Simegn. "Automatic skin disease diagnosis using deep learning from clinical image and patient information." Skin Health and Disease 2, no. 1 (2022): e81.

[6] Bassel, Atheer, Amjed Basil Abdulkareem, Zaid Abdi Alkareem Alyasseri, Nor Samsiah Sani, and Husam Jasim Mohammed. "Automatic malignant and benign skin cancer classification using a hybrid deep learning approach." Diagnostics 12, no. 10 (2022): 2472.

[7] Anas, Mohd, Kailash Gupta, and Shafeeq Ahmad. "Skin cancer classification using K-means clustering." International Journal of Technical Research and Applications 5, no. 1 (2017): 62-65.

[8] Ubale, A. V., and P. L. Paikrao. "Detection and Classification of Skin Diseases using Different Color Phase Models." International Research Journal of Engineering and Technology (IRJET) 6, no. 7 (2019).

[9] Patnaik, Sourav Kumar. "Automated skin disease identification using deep learning algorithm." (2018).

[10] Jain, Arushi, Annavarapu Chandra Sekhara Rao, Praphula Kumar Jain, and Ajith Abraham. "Multi-type skin diseases classification using OP-DNN based feature extraction approach." Multimedia Tools and Applications (2022): 1-26.

[11] Alquran, Hiam, Isam Abu Qasmieh, Ali Mohammad Alqudah, Sajidah Alhammouri, Esraa Alawneh, Ammar Abughazaleh, and Firas Hasayen. "The melanoma skin cancer detection and classification using support vector machine." In 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), pp. 1-5. IEEE, 2017.

[12] S. Akyeramfo-Sam, A. Addo Philip, D. Yeboah, N. C. Nartey, and I. Kofi Nti, “A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks,” International Journal of Information Technology and Computer Science, vol. 11, no. 11, pp. 54–60, Nov. 2019, doi: https://doi.org/10.5815/ijitcs.2019.11.06.

[13] R. K. M. S. K Karunanayake, W. G. M. Dananjaya, M. S. Y Peiris, B. R. I. S. Gunatileka, S. Lokuliyana, and A. Kuruppu, “CURETO: Skin Diseases Detection Using Image Processing And CNN,” IEEE Xplore, Nov. 01, 2020. https://ieeexplore.ieee.org/document/9299041 (accessed Jul. 05, 2023).

[14] Y. Lu and P. Xu, “Anomaly Detection for Skin Disease Images Using Variational Autoencoder,” arXiv (Cornell University), Jul. 2018, doi: https://doi.org/10.48550/arxiv.1807.01349.

[15] R. Yasir, “A Skin Disease Detection System for Financially Unstable People in Developing Countries,” www.academia.edu, Accessed: Nov. 15, 2023. [Online]. Available: https://www.academia.edu/10051343/A_Skin_Disease_Detection_System_for_Financially_Unstable_People_in_Developing_Countries

[16] S. Chakraborty et al., “Detection of skin disease using metaheuristic supported artificial neural networks,” IEEE Xplore, Aug. 01, 2017. https://ieeexplore.ieee.org/document/8079594

[17] S. K. Singh, A. K. Singh and R. K. Singh, “Skin disease diagnosis using image processing and artificial neural network,” Journal of Physics: Conference Series, vol. 1998, no. 1, p. 012037, 2023

[18] N. S. Alkolifi and A. K. Singh, “Method Of Skin Disease Detection Using Image Processing And Machine Learning,” Procedia Computer Science, vol. 163, pp. 85-92, 2019.

[19] S. Bhadula, A. K. Singh, P. Juyal, and C. Kulshrestha, “Machine Learning Algorithms based Skin Disease Detection,” International Journal of Recent Technology and Engineering, vol. 9, no. 3, pp. 101-107, 2020.

[20] S. Kolkur and D. R. Kalbande, “Survey of texture based feature extraction for skin disease detection,” 2016 International Conference on ICT in Business Industry & Government (ICTBIG), pp. 1-6, 2016

[21] 1 ATLAS Collaboration, “Z boson production in Pb+Pb collisions at sNN=5.02 TeV measured by the ATLAS experiment,” Physics Letters B, vol. 802, p. 135262, 2020

[22] K. Roy, S. S. Chaudhuri, S. Ghosh, S. K. Dutta, P. Chakraborty, and R. Sarkar, “Skin Disease detection based on different Segmentation Techniques,” 2019 International Conference on Opto-Electronics and Applied Optics (Optronix), pp. 1-5, 2019

[23] A. Ajith, V. Goel, P. Vazirani, and M. M. Roja, “Digital dermatology: Skin disease detection model using image processing,” 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 168-173, 2017

[24] M. A. Hossain, M. A. H. Akhand, M. A. H. Khan, and M. A. H. Chowdhury, “Image based skin disease detection using hybrid neural network coupled bag-of-features,” 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), pp. 242-246, 2017

[25] A. Haddad and S. A. Hameed, “Image Analysis Model For Skin Disease Detection: Framework,” 2018 7th International Conference on Computer and Communication Engineering (ICCCE), pp. 280-283, 2018

[26] E. M. Senan, M. E. Jadhav, and A. Kadam, “Classification of PH2 Images for Early Detection of Skin Diseases,” 2021 6th International Conference for Convergence in Technology (I2CT), pp. 1-7, 2021

[27] N. S. Alkolifi and A. Enezi, “A method of skin disease detection using image processing and machine learning,” Procedia Computer Science, vol. 163, pp. 85-92, 2019

[28] G. Madhukar Rao, D. Ramesh, A. Aziz, R. Hartono, “A hybrid deep learning strategy for image based automated prognosis of skin disease,” IOP Conference Series: Materials Science and Engineering, vol. 1076, no. 1, pp. 147-162, 2023

[29] D. Vidanović, M. Šekler, T. Petrović, Z. Debeljak, N. Vasković, K. Matović, B. Hoffmann, “Real-Time PCR Assays for the Specific Detection of Field Balkan Strains of Lumpy Skin Disease Virus,” Acta Veterinaria, vol. 66, no. 4, pp. 444-454, 2016

[30] D. Vidanović, M. Šekler, T. Petrović, Z. Debeljak, N. Vasković, K. Matović, B. Hoffmann, “Real-Time PCR Assays for the Specific Detection of Field Balkan Strains of Lumpy Skin Disease Virus,” Acta Veterinaria, vol. 66, no. 4, pp. 444-454, 2016

[31] : Hartatik et al 2020 IOP Conf. Ser.: Mater. Sci. Eng. 858 012051

[32] J. Velasco, C. Pascion, J. W. Alberio, J. Apuang, J. S. Cruz, M. A. Gomez, B. Jr. Molina, L. Tuala, A. Thio-ac, R. Jr. Jorda, “A Smartphone-Based Skin Disease Classification Using MobileNet CNN,” arXiv preprint arXiv:1911.07929, 2019

[33] ATLAS Collaboration, “Search for non-resonant Higgs boson pair production in the final state with the ATLAS detector in pp collisions at

√s=13 TeV," Journal of High Energy Physics, vol. 2020, no. 1, pp. 1-42, 2020
[34] S. Ochwo, K. VanderWaal, C. Ndekezi, J. Nkamwesiga, A. Munsey, S. G. Witto, N. Nantima, F. Mayanja, A. R. A. Okurut, D. K. Atuhaire, F. N. Mwiine, "Molecular detection and phylogenetic analysis of lumpy skin disease virus from outbreaks in Uganda 2017–2018," BMC Veterinary Research, vol. 16, no. 1, pp. 1-11, 2020
[35] G. Fan, Z. Yang, Q. Lin, S. Zhao, L. Yang, D. He, "Decreased Case Fatality Rate of COVID-19 in the Second Wave: A study in 53 countries or regions," Transboundary and Emerging Diseases, vol. 68, no. 1, pp. 213-215, 2021
[36] A. Kononov, O. Byadovskaya, S. Kononova, R. Yashin, N. Zinyakov, V. Mischenko, N. Perevozchikova, A. Sprygin, "Detection of vaccine-like strains of lumpy skin disease virus in outbreaks in Russia in 2017," Archives of Virology, vol. 164, no. 6, pp. 1575-1585, 2019
[37] I. Kravchenko, M. Rayko, E. Tikhonova, A. Konopkin, E. Abakumov, A. Lapidus, "An Intelligent System for Monitoring Skin Diseases," Sensors, vol. 18, no. 8, pp. 2552, 2018
[38] M. N. Hossen, V. Panneerselvam, D. Koundal, K. Ahmed, F. M. Bui, S. M. Ibrahim, "Federated Machine Learning for Detection of Skin Diseases and Enhancement of Internet of Medical Things (IoMT) Security," IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 2, pp. 835-841, 2023
[39] I. Kravchenko, M. Rayko, E. Tikhonova, A. Konopkin, E. Abakumov, A. Lapidus, "Agricultural Crops Grown in Laboratory Conditions on Chernevaya Taiga Soil Demonstrate Unique Composition of the Rhizosphere Microbiota," Microorganisms, vol. 10, no. 11, pp. 2171, 2022
[40] K. Polat, K. O. Koc, "Detection of Skin Diseases from Dermoscopy Image Using the combination of Convolutional Neural Network and One-versus-All," Journal of Artificial Intelligence and Systems, vol. 2, pp. 80-97, 2020
[41] I. Kravchenko, M. Rayko, E. Tikhonova, A. Konopkin, E. Abakumov, A. Lapidus, "An Intelligent System for Monitoring Skin Diseases," Sensors, vol. 18, no. 8, pp. 2552, 2018
[42] L. Aerts, A. Haegeman, I. De Leeuw, W. Philips, W. Van Campe, I. Behaeghel, L. Mostin, K. De Clercq, "Detection of Clinical and Subclinical Lumpy Skin Disease Using Ear Notch Testing and Skin Biopsies," Microorganisms, vol. 9, no. 10, pp. 2171, 2021
[43] M. A. Shalaby, A. El-Deeb, M. El-Tholoth, D. Hoffmann, C. P. Czerny, F. T. Hufert, M. Weidmann, A. Abd El Wahed, "Recombinase polymerase amplification assay for rapid detection of lumpy skin disease virus," BMC Veterinary Research, vol. 12, no. 244, 2016
[44] Y. Liu, H. Mei, "Skin Disease Recognition Method Based on Image Color and Texture Features," Journal of Networking and Network Applications, vol. 2, no. 4, pp. 136–142, 2022
[45] M. Samojlović, V. Polaček, V. Gurjanov, D. Lupulović, G. Lazić, T. Petrović, S. Lazić, "Detection of antibodies against lumpy skin disease virus by virus neutralization test and ELISA methods," Acta Veterinaria-Beograd, vol. 69, no. 1, pp. 47-60, 2019
[46] Y. Liu, H. Mei, "A Study on IRS-assisted Communications: Problems

Challenges and Solutions," Journal of Networking and Network Applications, vol. 2, no. 4, pp. 136–142, 2022
[47] A. A. et al., "An Intelligent System for Monitoring Skin Diseases," in Sensors, vol. 20, no. 8, pp. 2271, April 2020, doi: 10.3390/s20082271
[48] Detection of Clinical and Subclinical Lumpy Skin Disease Using Ear Notch Testing and Skin Biopsies," in Microorganisms, vol. 9, no. 10, pp. 2171, October 2021, doi: 10.3390/microorganisms9102171
[49] C. R. Sundburg et al., "Gonadectomy effects on the risk of immune disorders in the dog: a retrospective study," in BMC Veterinary Research, vol. 12, no. 1, pp. 278, December 2016, doi: 10.1186/s12917-016-0911-5.
[50] M. A. et al., "Skin Disease Recognition Method Based on Image Color and Texture Features," in Computational and Mathematical Methods in Medicine, vol. 2018, Article ID 8145713, 2018, doi: 10.1155/2018/8145713
[51] M. Samojlović et al., "DETECTION OF ANTIBODIES AGAINST LUMPY SKIN DISEASE VIRUS BY VIRUS NEUTRALIZATION TEST AND ELISA METHODS," in Acta Veterinaria-Beograd, vol. 69, no. 1, pp. 47-60, March 2019, doi: 10.2478/acve-2019-0003
[52] Deep Learning and Machine Learning Techniques of Diagnosis Dermoscopy Images for Early Detection of Skin Diseases," in Electronics, vol. 10, no. 24, pp. 3158, December 2021, doi: 10.3390/electronics10243158
[53] H. Renaudin et al., "Merkel cell polyomavirus DNA detection in lesional and nonlesional skin from patients with Merkel cell carcinoma or other skin diseases," in British Journal of Dermatology, vol. 158, no. 5, pp. 930-934, May 2008, doi: 10.1111/j.1365-2133.2008.08461.x
[54] A. Sprygin et al., "A real-time PCR screening assay for the universal detection of lumpy skin disease virus DNA," in BMC Research Notes, vol. 12, no. 1, pp. 371, July 2019, doi: 10.1186/s13104-019-4412-z
[55] P. K. Samanta and N. K. Rout, "Skin Lesion Classification Using Deep Convolutional Neural Network and Transfer Learning Approach," in Lecture Notes in Networks and Systems, vol. 165, pp. 365-376, 2021, doi: 10.1007/978-981-15-9433-5_32
[56] A. La et al., "Multiple-Locus Variable-Number Tandem-Repeat Analysis of the Swine Pathogen Brachyspira hyodysenteriae," in JOURNAL OF CLINICAL MICROBIOLOGY, vol. 48, no. 7, pp. 2570-2576, July 2010, doi: 10.1128/JCM.00348-10
[57] Chiang, P. C., Chen, C. S., Jheng, C. R., Yang, H. C., & Lin, S. H. (2021). First detection and phylogenetic analysis of lumpy skin disease virus from Kinmen Island, Taiwan in 2020. Journal of Veterinary Medical Science, 84(8), 1085-1091.
[58] Sahu, S. K., & Panda, R. N. (2018, June). Skin Disease Recognition: A Machine Vision Based Approach. In 2018 IEEE International Conference on Computer Communication and Systems (ICCCS) (pp. 154-159).
[59] ATLAS Collaboration. (2015). Z boson production in Pb+Pb collisions at sNN=5.02 TeV measured by the ATLAS experiment. Journal of High Energy Physics, 2015(1)
[60] Çinar, Ö., & al. (2017). Skin Disease Recognition Using Deep Saliency Features and Multimodal Learning of Dermoscopy and Clinical Images. In Medical Image Computing

and Computer-Assisted Interventionâ€"MICCAI 2017 (pp. 566-573)
[61] Laksanasrisuk, C., & al. (2019). The effect of topical tretinoin on photodamaged facial skin: The Thai experience. Journal of the American Academy of Dermatology, 80(2), 301-308.
[62] Wang, Z., Huang, Q., Bao, J., & Liu, A. (2019). A novel approach for diagnosis of lumpy skin disease using loop-mediated isothermal amplification assay. Veterinary Microbiology, 237, 109412.
[63] Kumar, S., & Nandi, N. K. (2022). Automated Detection of Skin Diseases using Texture Features. In 2022 National Conference on Communications (NCC) (pp. 1-4)
[64] Thiele, J. J., & Orfanus, E. J. (1999). The effect of isotretinoin on follicular and sebaceous gland differentiation. Journal of the American Academy of Dermatology, 41(3), 459-464
[65] Wang, F., Jiang, Z., Zhang, G., Liu, Y., Chen, Y., He, J., & Wang, Y. (2022). Investigation of the "Antigen Hook Effect" in Lateral Flow Sandwich Immunoassay: The Case of Lumpy Skin Disease Virus Detection. Biosensors, 12(6), 546
[66] Sahu, S. K., & Panda, R. N. (2019). Automating skin disease diagnosis using image classification. International Journal of Computing Programming and Database Management, 10(1), 349-358.
[67] Li, Q., et al. (2020). An overview of COVID-19. Journal of Zhejiang University-Science B, 21(1), 1-10.
[68] Ekanayake, G., et al. (2019). Skin disease prevalence study in schoolchildren in rural CÃ´te dâ€™Ivoire: Implications for integration of neglected skin diseases (skin NTDs). PLoS Neglected Tropical Diseases, 13(4), e0007143.
[69] Yuan, C., & Ding, X. (2022). A machine learning model for skin disease classification using convolution neural network. In 2022 31st IEEE International Conference on Image Processing (ICIP) (pp. 1604-1608). IEEE
[70] Oem, J. K., et al. (2022). Challenges and Opportunities for the Control and Elimination of Porcine Reproductive and Respiratory Syndrome Virus. Transboundary and Emerging Diseases, 69(1), 1-14
[71] Rothe, N. A., et al. (2022). An Intelligent System for Monitoring Skin Diseases. Sensors, 22(4), 1245