



Detection Of Various Skin Diseases: A Review

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Abstract: Our skin is one of the important parts of our body that covers and protects our internal parts. While doing so our skin can get affected by various allergies, irritants or diseases which can lead to a skin condition. Skin disease is one of the conditions which affects our skin and cause various kind of skin related problems. We have come across various kind of skin diseases which involves a wide range of varieties while some of them can leave a permanent mark on our skin and some don't. If it's not cured early skin diseases can also cause a social impact on a patient. With the various advancement in the field of image processing and detection techniques these diseases can be detected early and cured. In this paper we have explored number of such papers related to various kind of diseases that uses machine learning and deep learning models to detect them.

Keywords: *Skin diseases, image processing, deep learning, CNN, AlexNet, Monkeypox, Acne*

I. INTRODUCTION

In recent years, we are facing a lot of challenges especially in the field of medical science and one of those challenges is skin related problems. The main factor behind skin problems are skin diseases and other environmental factors. Skin diseases is mostly caused by virus, fungal, bacterial infection and allergies [1].

If it's not cured early and properly it can lead to skin related issues like leaving a permanent mark or larger skin pores. Several papers have done research work in the field of detection of various skin related diseases, detection of cancer and others like monkeypox, chickenpox etc. We have gone through those papers and have summarized their overall process and outcome in this paper. These papers include several types of diseases and some of them are as follows:

After a global pandemic caused by SARS-COV-2 or 2019-nCov virus (COVID-19) another virus came into the picture that is Monkeypox. Monkeypox a member of the orthopoxvirus genus. Firstly, identified in monkey in 1959 at a research institute in Denmark. Later, the first human case was confirmed in the Republic of Congo in 1970 when a child with smallpox like symptoms was admitted in a hospital [1]. It's an infectious disease which transmits itself whenever a person comes close with another infected individual (direct body contact), through bites, droplets or mucous of the eye, nose or mouth.

Similarly, Chickenpox is a disease which is caused by varicella-zoster virus or VZV. Most people will get the virus when they're in their early stage, have a weak immune system or haven't had a chickenpox vaccine. Children in temperate regions are likely to get chickenpox than adults, with children in primary level or younger being most at risk [12]. It can spread through close contact with an infected individual, cold, cough [15].

Measles is an infectious disease that's caused by measles virus. It causes a skin rash and can spread to others through coughing and sneezing. It is a childhood infection and can be prevented by a vaccine. It can be serious or even alerting for small children. Measles sign and symptoms include fever, dry cough, running nose, sore throat, conjunctivitis and skin rash made up of large blotches [16].

Melanoma is a skin cancer that develops in the cells(melanocytes) that produces melanin. Melanin gives colour to our skin. Melanoma can form in back, legs, arms, face and can rarely form inside our body like nose or throat. Ultraviolet radiation from sun, tanning lamps and beds can increase the risk of developing melanoma. The risk of melanoma seems to be increasing in people who are under 40 and especially women. It can be treated successfully if detected early [17]. It is classified into two types benign and malignant melanoma.

Main cause of Ringworm is a fungal infection. It's usually a circular rash where middle skin is clearer. It got the name because of its appearance and its not caused by a worm. Ringworm often spreads by direct contact with infected persons or animals. Its symptoms are a scaly ring-shaped area, itchiness, a round flat patch of itchy skin etc. It can be cured by antifungal medications [18].

Acne is a skin condition where pores of our skin get blocked. It's responsible for causing pimples, whiteheads and blackheads. It's very common among teenagers. Pimples and bumps heal slowly. Acne can leave a mark or scar a skin. Effective treatment can cure it and if it's done earlier, it can be cured easily and won't leave any marks [19].

If these diseases are not cured properly then they can be fatal, leave a mark on a skin which can affect an individual state of living. To avoid that from happening it needs to be treated properly. This is where computer vision or image processing can play an important role. With the advancement and improvement of various image detection models, detection of skin diseases can be done much more efficiently and accurately. Various deep learning and machine learning approaches were used by researchers to detect these diseases and we will be discussing about them on upcoming sections.

The remaining structure of paper is divided as follows. Section 2 contains the literature survey along with a comparison table and Section 3 contains the conclusion part.

II. LITERATURE SURVEY

There are several research papers that have implemented various image processing techniques to detect various kinds of diseases and viruses. Review of the literature on these papers has contributed to our understanding.

Authors, C. Sitaula. et al [1], proposed to detect monkeypox virus, chickenpox and measles with 13 pre-trained deep learning models. These pre-trained model ranges from heavy-weight DL models such as VGG-16, InceptionV3 and Xception to light-weight models such as MobileNet, and EfficientNet. They collected publicly available Monkeypox image data, this dataset has different sub-folders, that include datasets with and without augmentations. They fine-tuned these pre-trained deep learning models with custom layers and for evaluation they used metrics like F1-score, precision, recall and accuracy. For implementation they resized each image into 150*150 pixels. For augmentation they tuned the parameters as follows rescale=1/255, rotation range=50, width shift range=0.2, height shift range=0.2, shear range=0.25, zoom range=0.1, and channel shift range=20. They designed random five folds (5-cross validation), where each fold contains 70/30 for train and test ratio and reported the average performance. To ensemble multiple Deep learning models, they extracted probabilistic values from each pre-trained models and perform the majority voting approach. Out of these models Xception is the second-best performing model with Precision: 85.01%, Recall: 85.14%, F1-score: 85.02%, and Accuracy: 86.51% and their ensemble approach provides the highest performance with precision 85.44%, Recall 85.47%, F1-score 85.40% and accuracy 87.14% along with that it also provides explainability of DL model using LIME (Local Interpretable model-agnostic explanations) and Gradient-weighted Class Activation Mapping (Grad-CAM).

In this work, authors, S . A. AlDera, et al [2], worked on classification and diagnosis of skin diseases like acne, cherry angioma, melanoma, and psoriasis. They used three machine learning algorithms i.e. Supported Vector Machine, Random Forest and K-Nearest Neighbor classifiers before that various image processing methods were used and they are acquiring images, preprocessing images, i.e., resizing images-this consist of resizing the image to 250*250 pixels, color transformation, de-noising-here they used a technique known as median filter, normalization, segmentation, and feature extraction-It involved Gabor and Entropy techniques to extract texture features and Sobel technique for edge features. They gathered images from available resources like dermnet NZ and atlas dermatologico. Their dataset consists of 377 images and it have 4 classes that is acne, cherry angioma, melanoma and psoriasis. They split the dataset into 80% for training and 20%

for testing that is 301 images for the train set and 76 images for the test set. The model performance was analyzed by number of measuring techniques and they are F1-score, Recall, Precision and Accuracy. Among the three classifiers, SVM gave an accuracy rate of 90.7%, Random Forest (RF) gave an accuracy of 84.3% and K-Nearest Neighbor(K-NN) gave an accuracy of 84.2%.

Authors, M. M. Ahsan, et al [3], worked on detection of Monkeypox virus that was implemented on modified VGG16 model. Monkeypox image data was collected from various sources such as websites, newspapers, and online portals and publicly shared samples and for non-Monkey pox they used images of Chickenpox, Measles. After doing this they uploaded a Monkeypox image dataset to GitHub which can be accessed by anyone. Initially their dataset consists of 164 samples which were increased to 1915 samples using data augmentation. Data augmentation involved Width shift up to 2%, Rotation Range: 0° - 45° , Zoom range of 2%, Height shift: Up to 2%, Shear range: of 2%, Fill mode: Reflective and Horizontal flip was set to True. To evaluate the performance of model on developed dataset transfer learning approach was used for pilot test. Their core model consists of 3 essential parts and they are pre-trained architecture, an updated layer and prediction class. Their modified layer flattened the architecture and that was followed by 3 dense and 1 dropout layer. It includes two distinct study. Study one and study two had a different Batch size, learning rate, Number of Epochs.80:20 ratio was followed to divide training and testing dataset. They also used Local Interpretable model-agnostic explanations (LIME) to validate their findings. Study one gave an accuracy of $97 \pm 1.8\%$ (AUC = 97.2) and study two gave an accuracy of $88 \pm 0.8\%$ (AUC = 0.867).

In this research work, S. N. Ali, et.al [4], worked on detection of monkeypox and other diseases like chickenpox and measles. They used three models to do so and they are VGG-16, ResNet50 and Inception v3. They used publicly available case reports, news portals, and websites to gather their dataset. After gathering data, they developed an open-source Monkeypox Skin Lesion Dataset (MSLD). Their work mainly focuses on distinguishing Monkeypox cases from similar non-monkeypox cases. They discarded low-quality images and out-of-focus images, after this those images were resized to $224*224$ pixels. Total 228 images were collected out of which 102 belongs to Monkeypox and remaining 126 represented chickenpox and measles. Several augmentation methods were used which increased the image data set to 1423 for Monkeypox and 1764 for others. Augmentation is used to increase the size of data and this paper uses several augmentation methods they are rotation, translation, reflection, contrast, brightness jitter, saturation, hue, shear, noise, and scaling. Images were split into training set, testing set and validation set i.e.,70:10:20 ratio. An ensemble of these 3 models was also developed. Authors also developed a prototype web-app for monkeypox screening. Out of these ResNet50 gave an accuracy of 82.96 ($\pm 4.57\%$), VGG16 gave an accuracy of 81.48 ($\pm 4.57\%$), InceptionV3 gave an accuracy of 74.07($\pm 3.78\%$) and ensemble system achieved an accuracy of 79.26 ($\pm 1.05\%$).

Authors M. N. Bajwa et al., [5], worked on various pre-trained Deep learning CNN models to detect skin diseases. To do so they used two publicly available skin image datasets and they are DermNet and ISIC Archive (2018 version). DermNet consist of around 23,000 images and out of these they used 22,501 images. It has 23 super-classes of diseases which are divided into 642 subclasses. Since it contained duplicate, empty and irrelevant data they removed them and end up with 21,844 images of 622 subclasses. Similarly, ISIC consists of 24,000 images that are divided into 7 classes. After gathering dataset, they selected 4 CNN models and they are ResNet-152, DenseNet-161, SE-ResNeXt-101, and NASNet. For ensemble, the average of individual prediction of these models were considered and output the final prediction. To divide dataset into training and testing set they used stratified k-fold cross validation where the value of k was set to 5. They got an accuracy of 80% and AUC of 98% for classification of 23 diseases on DermNet. They also set precedence for classifying all 622 sub-classes and got 67% accuracy and 98% AUC. On ISIC dataset they classified 7 diseases and got an average accuracy of 93% and 99% AUC.

In this T. Shanthi et al., [6] used a Convolutional Neural Network (CNN) to recognize and classify skin diseases present in human body using skin disease images. For this they used a DermNet database which contains number of diseases out of which they have considered 4 different types of skin diseases and they are acne, keratosis, eczema herpeticum, urticaria and each class contains 30 to 60 different samples. Dataset consists of 174 images and it was divided into two phase training and testing. Training involved 105 images and testing used 69 images. AlexNet was used to detect and categorized different skin diseases in human body. It has several layers like Fully Connected layer, pooling layer, convolution layer, Rectified Linear Unit layer. Their model achieved 96.32% for training accuracy (dataset) and 62.1% for validation accuracy (10% of training dataset).

V. R. Allugunti [7], worked on a deep learning technique (CNN) for diagnosing melanoma that is present at a preliminary phase A CNN model for diagnosing skin cancer was created and trained on a melanoma dataset. Dataset was gathered from DermNet and it includes 3 types of melanoma images and they are lesion malignant, superficial spreading, and nodular melanoma. To avoid the overfitting of data, data augmentation was used. Zoom effect was added for image enhancement. This model makes a distinction among lesion malignant, superficial spreading and nodular melanoma. For analysis researcher considered ML algorithms and DL algorithms and they are DT, RF GBT and CNN. Out of these models CNN accuracy was higher than the rest i.e., 88.83% whereas other classifier accuracy was 67% ,71% and 73.44% respectively.

In [8], researchers explored Multi-Class Multi-Level (MCML) algorithm that is inspired by divide and conquer rule to provide a multi-class classification of skin disease. This paper focuses on detection of skin cancer. Skin Lesion classification problem is divided into sub-problems and these are solved in multiple steps rather than solving it in one step because of this classification performance is increased. Two approaches, traditional machine learning approach and deep learning approach were used to implement MCML. Traditional machine learning approach involves improved techniques for removing black frames, circles. MCML performance was also compared with Multi-Class Single-Level algorithm. Images were collected from various sources and they are International Skin Imaging Collaboration (ISIC) Dermoscopic Archive, PH2 dataset, 11 K hand's, DermIS, DermQuest and DermNZ. Numbers of samples were brought down to same size to avoid data imbalance. Their dataset consists of 4 classes and they are Healthy, Benign, Malignant and Eczema. Each of these classes have 918 images. Dataset was divided into training (602 images for every class) and testing (258 images for every class) scheme in the ratio of 70:30 in order to test the models of MCSL and MCML algorithms. 58 (images for every class) were used for comparing MCSL and MCML classification algorithm performance. Traditional machine learning approach involves 4 steps pre-processing, segmentation, feature extraction and classification. Pre-processing removes noise such as black frames, circles and hairs. Segmentation involves extracting the ROI from images using a hybrid technique of k-means clustering, morphological erosion operation and Otsu's thresholding. Feature extraction involves extraction of geometric, colour and texture features from the ROI and for classification they used an ANN. For performing MCSL and MCML classification using deep learning method transfer learning approach and a pre-trained model AlexNet is used. Total of 3672 images were used and MCML algorithm achieved an accuracy of 96.47% which outperforms the MCSL classification algorithm.

[9], here researchers explored Deep learning models to classify skin disease. They have used MobileNet V2 and Long Short-Term Memory (LSTM) to do so. MobileNet-V2 proved to be efficient with better accuracy that can work on lightweight devices too [10]. A grey-level co-occurrence matrix was used to assess the progress of disease growth. This model was compared against number of other models like Fine-Tuned Neural Networks (FTNN), Convolutional Neural Network (CNN), Very Deep Convolutional Networks for Large-Scale Image Recognition developed by Visual Geometry Group (VGG) and CNN architecture that expanded with few changes. They used HAM10000 dataset which consists of 7 skin diseases and they are Melanocytic nevi, Benign keratosis-like lesions, Dermatofibroma, Vascular lesions, Actinic keratoses, Intraepithelial carcinoma, Basal cell carcinoma, and Melanoma. Dataset consist more than 10,000 images and there was an imbalance in the number of skin images in each type of lesion. To avoid this, they used data augmentation techniques and dataset was divided into three parts training data 85%, testing data 10% and validation data 5%. The input size of image accepted by model is 224*224 pixel. LSTM is a component used with recurrent neural network. It's capable of learning pattern estimation problems. Memory blocks are managed by memory cells that consist input, outlet gate, forgotten gate and window connection encompassed in the abstract of LSTM layer [9]. Performance is evaluated using metrics like Sensitivity, Specificity, Accuracy, JSI, and the MCC. MobileNet v2-LSTM approach proved to be efficient for classification and detection with minimal computational power and effort. They got an accuracy of 85.34 %.

Authors M. Altun et al [10], worked on detection of monkeypox disease through skin lesions with the help of deep-learning methods. These methods used transfer learning tools and hyperparameter optimization was done. They used the latest version of transfer learning models such as EfficientNetV2s, MobileNetV3, VGG19, ResNet50, DenseNet, and Xception. They added intermediate layers and different activation functions to the model before the output layer. Hyperparameters of each model were also optimized, such as learning rate, batch size, dropout rate, and number of epochs. In case of dataset, it consists of 2 classes positive and negative. Only image data of skin lesions that belongs to monkeypox were added in positive folder and negative folder consists of skin lesions of Lyme, Drug Rash, Pityriasis Rosea Rash, and Ring Worm diseases. After augmentation 2056 images were obtained out of which 1742 images were used for training, in this 1200 images were positive lesions and 542 images were negative lesions. For test 156 images were used out of which 90 were positive lesions and 66 were negative lesions. They used Kaggle to obtain test data and to

collect other data they used cloud and big data. Data augmentation involves Flip (Horizontal, Vertical), 90° Rotate (Clockwise, Counter-Clockwise, Upside Down). They used number of metrics to measure the performance of model and they are MSE, AUC, accuracy, loss function, and F1-score. Hybrid MobileNetV3-s achieves the best results, with an average F1-score of 0.98, AUC of 0.99, accuracy of 0.96, and recall of 0.97. They also showed that the hybrid MobileNetV3-s model outperforms the other models in terms of training time and memory usage.

In this research work authors D. Uzun Ozsahin et al [11], worked on training and validating a Deep learning-based model that is capable of detecting and classifying monkeypox and chickenpox using digital images and the performance of DL model was compared with other state of the art pre-trained models. To collect monkeypox images authors used a dataset of previous studies and the chickenpox dataset was obtained from publicly available case reports. Monkeypox have 102 images and chickenpox have 240 images which are very small hence they used data augmentation and after this they got 10,000 images of each class. They designed a CNN model and improved it by adding layers (convolution, pooling and dense) and tuning a hyperparameter. Their model is a 2D CNN architecture which consists of 4 convolutional and 3 max-pooling layers are applied after the 2nd and 4th convolutional layers. Two layers use kernel sizes of 3*3 and 2*2 respectively. Two fully connected layers with 64 and 2 units provided high-level reasoning before the final sigmoid classifier layer. Relu was the activation function of choice across the network before the final sigmoid activation function. While training the CNN they used a part of training set as a validation dataset and tested the model accuracy on unseen dataset. They compared the performance of the proposed model with the state of art pre-trained models, including VGG16, VGG19, ResNet50, AlexNet, and InceptionV3. Their proposed CNN model outperformed all DL models with a test accuracy of 99.60% and weighted average precision, recall, F1 score of 99.00% was recorded.

Authors D. Bala et al [12], present a novel approach to detect a monkeypox virus. They proposed a modified Deep learning model that uses a pretrained CNN model DenseNet-201 as a foundation of their network and named their model as MonkeyNet. They claimed that MonkeyNet, can achieve high accuracy and robustness in detecting and classifying monkeypox cases. To test their model, they created an open source Monkeypox Skin Images Dataset (MSID) which consists several types of images that were gathered from variety of open-source and online sources. This dataset have 4 different image classes and they are monkeypox, chickenpox, measles and normal images. Data preprocessing included image resizing, normalization and converting labels to categories. Since number of images were lower, they used data augmentation to expand the size of dataset. 80% of images were used for training and 20% for testing, from training dataset 20% of image samples was utilized for model validation. Model development stage included machine learning classifiers, pre-trained deep learning models and proposed CNN model. Machine learning classifiers included Logistic Regression, Random Forest, K-Nearest Neighbor, SVM and Extreme Gradient Boosting. In the 2nd round of classification, they used deep learning models in which each model was trained on trained dataset with its pretrained weights with a slight modification i.e., an extra 3 layers at the end of model that are flatten layer, dense layer and output layer with 4 classes was added and these deep learning models are VGG16, ResNet-50, MobileNetV1, Inception V3 and Xception. They used accuracy, precision, recall, AUC and F1-score to measure the performance of models. Overall accuracy of their proposed model is higher than other deep learning models with an accuracy of 93.19% and 98.91% in the multiclass classification of the original and augmented datasets respectively.

Authors M. E. Haque et al [13], integrated deep transfer learning-based methods along with a convolutional block attention module CBAM, proposed by S. Woo et al [32] to focus on the relevant portion of feature maps and to perform an image-based classification of human monkeypox disease. They used five deep learning models through transfer-learning-based models with the CBAM attention mechanism models and they are VGG19, Xception, DenseNet121, EfficientNetB3, and MobileNetV2 along with integrated channel and spatial attention mechanisms and perform a comparative analysis. In this they used Monkeypox Skin Lesion Dataset (MSLD) that was proposed by [4]. This dataset includes Monkeypox, chickenpox and measles, it includes original images and augmented folder images. So, researchers used augmented images for training and validation set and used original images for testing. All pre-trained models are modified with same method. Images of MSLD were resized to 224*224*3. They froze all last layers except the last two layers of pre-trained architectures. They used CBAM to utilize the most relevant parts of generated feature maps. CBAM has two sequential attention-based mechanisms and they are channel attention and spatial attention, the output from this was passed through two dense layers with ReLU activation function. The last dense layer uses

sigmoid activation to perform binary classification. To measure the performance of models they used evaluation metrics Accuracy, Precision, Recall and F1-Score. Xception-CBAM Dense architecture performed better than others with an accuracy, precision, recall and f1-score of 83.89%, 90.70%, 89.10%, and 90.11%, respectively

Comparison of these research work is provided below in table 1.

Table 1: Comparison table of existing techniques

Author	Title	Dataset	Classes	Models	Performance
C. Sitaula et al [1]	Monkeypox virus detection using pre-trained deep learning-based approaches.	Monkeypox image data was used.	4	13 pre-trained deep learning models and ensemble approach was used.	Ensemble approach precision:85.44%, Recall:85.47%, F1-score:85.40% and accuracy :87.14%.
S. A. Aldera et al [2]	A Model for Classification and Diagnosis of Skin Disease using Machine Learning and Image Processing Techniques.	Dermnet — NZ and Atlas dermatologico	4	Supported Vector Machine, Random Forest and K-Nearest Neighbor classifiers were used.	SVM accuracy: 90.7%, Random Forest (RF) accuracy: 84.3% and K-Nearest Neighbor(K-NN) accuracy: 84.2%.
M. M. Ahsan et al [3]	Image Data collection and implementation of deep learning-based model in detecting Monkeypox disease using modified VGG16.	Publicly available sources	3	Modified VGG16.	Study one gave an accuracy of $97 \pm 1.8\%$ (AUC = 97.2) and study two gave an accuracy of $88 \pm 0.8\%$ (AUC = 0.867).
S. N. Ali et al [4]	Monkeypox skin lesion detection using deep learning models A feasibility study.	Publicly available sources	3	VGG-16, ResNet50, ensemble system and Inception v3.	ResNet50 accuracy: ($\pm 4.57\%$), VGG16 accuracy: 81.48 ($\pm 4.57\%$), InceptionV3 accuracy: 74.07($\pm 3.78\%$)

					and ensemble system accuracy: 79.26 ($\pm 1.05\%$).
M. N. Bajwa et al [5]	Computer-Aided Diagnosis of Skin Diseases using Deep Neural Networks	DermNet and ISIC Archive (2018 version)	DermNet consist 23 super-classes of disease which are taxonomically divided into 622 unique subclasses and ISIC Archive consist of 7 classes.	ResNet-152, DenseNet-161, SE-ResNeXt-101, and NASNet	DermNet accuracy: 80% and 98% AUC for classification of 23 diseases. They also set precedence for classifying all 622 sub-classes and got 67% accuracy and 98% AUC. On ISIC dataset they classified 7 diseases and got an average accuracy of 93% and 99% AUC.
T. Shanthi et al [6]	Automatic diagnosis of skin diseases using convolution neural network	DermNet.	5	AlexNet	96.32% training accuracy (dataset) and 62.1% for validation accuracy (10% of training dataset).
V. R. Allugunti [7]	A machine learning model for skin disease classification using convolution neural network,	DermNet.	3	CNN	Accuracy:88.83%.
N. Hameed et al [8]	Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques	International Skin Imaging Collaboration (ISIC) Dermoscopic Archive, PH2 dataset, 11 K hand's, DermIS, DermQuest and DermNZ.	4	Multi-Class Multi-Level algorithm (MCML).	MCML accuracy:96.47%.
P. N. Srinivasu et al [9]	Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM.	HAM10000	8	MobileNet V2 and Long Short-Term Memory (LSTM)	Accuracy:85.34%.

M. Altun et al [10]	Monkeypox Detection Using CNN with Transfer Learning.	Kaggle, cloud and big data	5	EfficientNetV2s, MobileNetV3, VGG19, ResNet50, DenseNet, and Xception	Hybrid MobileNetV3-s average F1-score: 0.98, AUC: 0.99, accuracy: 0.96, recall: 0.97
D. Uzun Ozsahin et al [11]	Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesion in Human Subjects Using Deep Learning Framework.	Publicly available sources.	2	VGG16, VGG19, ResNet50, AlexNet, InceptionV3 and a proposed CNN model.	Proposed CNN model accuracy: 99.60% and weighted average precision, recall, F1 score of 99.00%.
D. Bala et al [12]	Monkeynet: A robust deep convolutional neural network for monkeypox disease detection and classification.	Publicly available sources.	4	MonkeyNet a modified version of DenseNet-201	Accuracy of 93.19% and 98.91% in the multiclass classification of the original and augmented datasets respectively.
M. E. Haque et al [13]	Classification of Human Monkeypox Disease Using Deep Learning Models and Attention Mechanisms.	Monkeypox Skin Lesion Dataset (MSLD) that was proposed by [4]	3	VGG19, Xception, DenseNet121, EfficientNetB3, and MobileNetV2	Xception-CBAM Dense architecture accuracy, precision, recall and f1-score of 83.89%, 90.70%, 89.10%, and 90.11%, respectively.

III. CONCLUSION

Several types of skin-related diseases will be encountered by humans and to recognize them quickly and accurately computer vision can play an important part especially machine learning and deep learning models as we have seen in the above section. Several types of models were used by researchers to detect number of diseases with a good accuracy rate. Skin is an important part of our body and life, it needs to be taken care and if not, it can affect individual's mental and social life. To avoid this from happening one must take care of them as soon as possible and get a medication or consult a professional. Here we have gone through number of research papers that have detected diseases like Monkeypox, Chickenpox, Measles, Ringworms, Cancer and Acne. There are several models where efficiency and accuracy were improved drastically by fine tuning various parameters or by adding new layers to a pre-defined model, number of papers used limited dataset which can be further explored by researchers to improve the accuracy rate.

With the enhancement of technology machine learning and deep learning have also improved drastically which can be a useful tool in the field of medical science and other fields. We believe that this review can

help researchers and professionals to get an idea about various models related to machine learning and deep learning that can be further expanded or refined to detect other diseases.

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