IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Detection of Monkeypox and Acne using AlexNet

Nitesh Rai[1], Prashansa Taneja[2], Mukesh Sharma[3] and Rehan Khan[4]

1. Research Scholar, (MTech Computer Science & Engineering) APG Shimla University Himachal Pradesh,
2. Assistant Prof. (Computer Science Engineering Department), APG Shimla University Himachal Pradesh,
3. Assistant Prof. (Computer Science Engineering Department), APG Shimla University Himachal Pradesh,
4. Assistant Prof. (Computer Science Engineering Department), APG Shimla University Himachal Pradesh,

***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 causes various kinds 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 diseases like monkeypox, acne and detected them successfully using AlexNet, a CNN deep learning model with an accuracy of 97.2%, precision of 98.9%, F1 score of 97.24% and recall of 95.64%.

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

I. INTRODUCTION

Skin, an important and the most crucial part of our body, but 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. With the advancement of computer vision machine learning and deep learning are playing an important role in detection of various kinds of diseases and this is supported by number of papers that have successfully implemented various machine learning and deep learning models to classify and detect diseases. For our work, we have considered two types of diseases and they are monkeypox and acne. 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 is 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 that 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.

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 detected earlier, it can be cured easily and won't leave any marks [19].

If these diseases are not cured properly then they can 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 similar types of diseases. When it comes to detection of diseases using images convolutional neural networks (CNN) have proved to provide good accuracy and it's the preferred deep learning model to do so. Considering the accuracy and detection capability of deep learning models than machine learning models, we have considered a pre-trained CNN deep learning model also known as AlexNet to detect monkeypox and acne. To get the maximum performance parameters such as learning rate, epochs, and loss functions were fine-tuned.

There are several authors who have implemented deep learning models for detection of various kinds of diseases and no other authors have worked on detection of two diseases acne and monkeypox. So, we gathered images of monkeypox and acne from various sources and performed data pre-processing, augmentation to improve and increase number of images. Contribution of our paper are as follows:

- To gather images and propose a dataset of monkeypox and acne disease which is splitted into training and testing sets.
- Secondly, improve and increase acne and monkeypox images to train and test our model in a large dataset.
- Thirdly, apply deep learning model i.e., AlexNet to recognize monkeypox and acne.
- Finally, measure the performance of model by various metrices likes Accuracy, Precision, Recall and F1 score.

The remaining structure of paper is divided as follows. Section 2 contains literature survey, Section 3 contains data collection, Section 4 defines methodology and model along with evaluation metrices, Section 5 contains results, Section 6 contains discussion and limitations of our work and Section 7 contains conclusion of our work.

II. LITERATURE REVIEW

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 metrices 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 ± 1.8% (AUC = 97.2) and study two gave an accuracy of 88 ± 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 (±4.57%), VGG16 gave an accuracy of 81.48 (±4.57%), InceptionV3 gave an accuracy of 74.07(±3.78%) and ensemble system achieved an accuracy of 79.26 (±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 maligna, 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 maligna, 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. Preprocessing 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 EffidientNetV2s, 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 metrices 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.

III. DATASET COLLECTION

In this study, we have considered two diseases and they are acne and monkeypox. To gather monkeypox images we used Monkeypox Skin Lesion Dataset (MSLD) developed by [4]. This dataset consists of monkeypox and other non-monkeypox images, non-monkeypox contain chickenpox and measles cases. MSLD consist of 3 folders and they are original images, Augmented images and Fold1 which contain three-fold cross validation datasets**.** Original images folder consists of 228 images out of which 102 belongs to monkeypox and 126 belongs to non-monkeypox (chickenpox and measles) for our work we considered monkeypox images from original images folder i.e., 102 images.

Similarly, to gather Acne images we used Kaggle and we found an Acne dataset. This dataset consists of 1833 images of acne and we used these images. After gathering both images we combined them in two different sets and they are testing set and training set. Both of these sets consist of two sub-folders and they are Acne and Monkeypox which consist of Acne and Monkeypox images respectively. Image samples of different diseases are provided in Fig 1 and Fig 2.

Figure 1: Acne image samples

Figure 2: Monkeypox image samples

IV. METHODOLOGY

The proposed work aims to detect Acne and Monkeypox using a deep learning model i.e., AlexNet. To avoid any inconsistency data preprocessing was used to remove noise from images. We used data augmentation to increase number of images. Dataset was splitted into two sections training and testing section. We used 80% of data for training our model and remaining 20% for testing our model. Afterwards to measure the model we used various metrices like Accuracy, Precision, Recall and F1 Score. Fig 3 shows our overall proposed methodology framework.

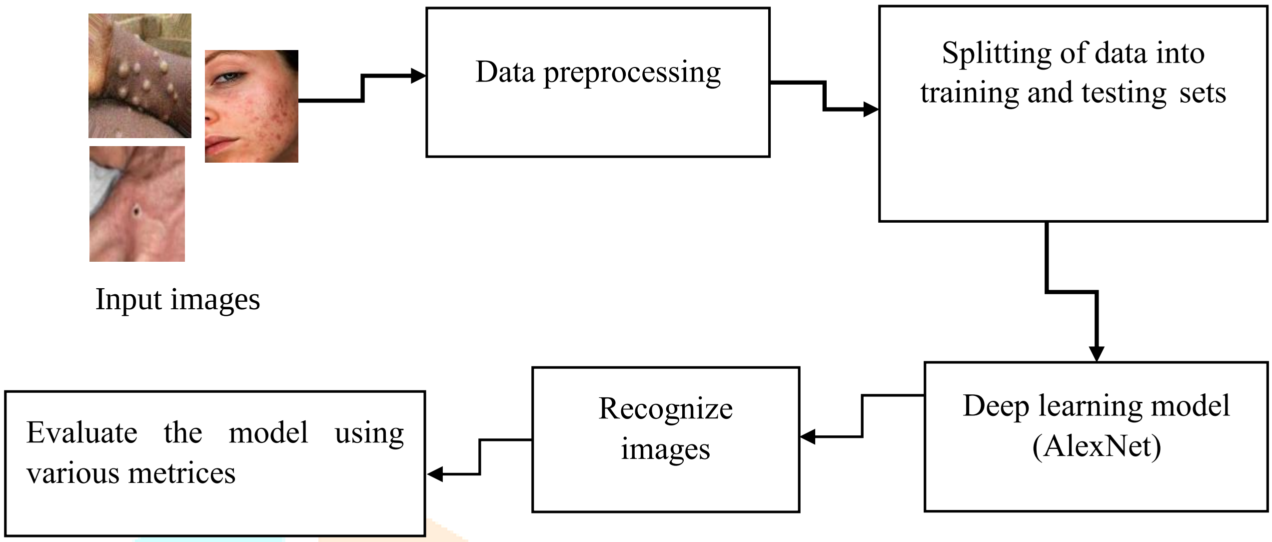

Figure 3: Proposed methodology architecture

4.1 DATA PREPROCESSING

4.1.1 Image preprocessing

Image preprocessing is an important and most crucial part that is used to enhance the quality of an image. While capturing an image it can get effected by noise or other factors and to remove this noise, we use image preprocessing. Followings were used in image preprocessing:

Feature scaling: The data preprocessing method known as "feature scaling" is employed in machine learning and entails scaling down the values of features or variables in a dataset. This prevents features with higher values from predominating the model and ensures that all features contribute evenly to the model. When working with datasets where the features have multiple ranges, units of measurement, or orders of magnitude, feature scaling is crucial. Standardization, normalization, and min-max scaling are common methods for feature scaling. Image preprocessing involves number of things like scaling of images, turning images to a RGB format, one-hot encoding the labels. We used normalization for our purpose.

Image resizing: Image resizing is also an important part of preprocessing. Images we gathered had different size and it was necessary to bring them in a same scale. Hence, images were resized to 227*227 pixels where 227 represents height and width of image and it's the required input image size of AlexNet.

One-hot encoding: A machine learning model can express categorical variables as numerical values using the one-hot encoding approach. Each potential category is represented by a new binary feature, and each sample's feature that matches to its original category 1 is given a value of 1. When dealing with machine learning algorithms that need numerical input, one-hot encoding is helpful since it enables the usage of categorical variables in these models.

4.1.2 Data augmentation

Data augmentation expands the amount of training and testing dataset that is used to train and test a model. Flexible image augmentations and geometric augmentations are examples of smart augmentation techniques that may be used to build unique picture augmentation libraries. We may make a number of adjustments to the starting data. Geometric transformations, for instance, can be used to arbitrarily flip, crop, rotate, or translate pictures. Additionally, we may alter RGB color channels and amplify any color using color space transforms. For our work we used various libraries of python to implement data augmentation and they are image data generator from keras, os, NumPy and io. Our dataset had inconsistency in number of images, to avoid that augmentation was used. For Monkeypox and Acne augmentation ratios were different and after augmentation 10,000 images were generated and each class have 5,000 images. 4000 images of each class were used for training and remaining 1000 images of each class were used for testing. We used various augmentation techniques and they are rotation, shear, zoom, horizontal flip, and brightness. Number of parameters used in data augmentation is given in table 1.

Table 1: Augmentation parameters used in our work

Parameters name
Rotation
Shear
Zoom
Horizontal
Brightness

After augmentation we got ample of images and data was splitted into training and testing part. We have provided details about number of images before and after augmentation on Table 2 and 3. Initially we had 1935 images and after augmentation we got 10,000 images.

Table 2: Number of images before augmentation

Classes	Training	Testing	Total
Monkeypox	82	20	102
Acne	1467	366	1833
	1549	386	1935

Table 3: Number of images after augmentation

Classes	Training	Testing	Total
Monkeypox	4000	1000	5000
Acne	4000	1000	5000
	8000	2000	10000

4.2 Data splitting

After preprocessing images were brought down to 227*227 pixels and after this data were splitted into two half and they are training and testing. We followed 80:20 ratio where 80% of data were used for training our model and remaining 20% of them were used for testing our model. Training set involved separate Acne and Monkeypox images and testing set followed the same.

4.3 Deep Learning Model

To implement our work, we used a deep learning model named as AlexNet to recognize Acne and Monkeypox image lesion. Architecture of AlexNet in show on fig 4. Alex Krizhevsky and his colleagues created the convolutional neural network (CNN) architecture known as AlexNet in 2012. With a top-5 error rate of 15.3%, it won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) that year. AlexNet is regarded as a turning point in deep learning since it showed that CNNs can perform at the cutting edge on challenging visual tasks like object recognition and categorization.

Eight layers make up AlexNet and they are three fully linked layers and five convolutional layers. Following a max-pooling layer of size 3x3 with a stride of 2 and a local response normalization layer, the first convolutional layer employs 96 filters of size 11x11 with a stride of 4. Another max-pooling and normalization layer comes after the second convolutional layer, which employs 256 filters with a stride of 1 and a size of 5x5. Without any pooling or normalization, the third, fourth, and fifth convolutional layers each employ 384, 384, and 256 filters, all of size 3x3, with a stride of 1. Two fully connected layers with 4096 neurons each come after the final convolutional layer, and then there is a final softmax layer with 1000 neurons for the output classes. The first and second fully connected layers uses dropout with a probability of 0.5 to reduce overfitting [6].

When compared to other CNN architectures AlexNet distinguished itself with a number of features. First, it avoids the vanishing gradient problem and speeds up training by using rectified linear units (ReLU) as the activation function rather than sigmoid or tanh. Second, to increase the quantity and diversity of the training data and enhance generalization, it employs data augmentation techniques including random cropping, flipping, and color modifications. Third, since each GPU manages part of the network, it parallelizes computing and lowers memory requirements by using two GPUs. Fourth, it optimizes the network parameters using a high learning rate along with a momentum term and a weight decay term.

Since it provided the foundation for numerous later research projects and applications utilizing CNNs and GPUs, AlexNet is recognized as one of the most influential publications in computer vision and deep learning.

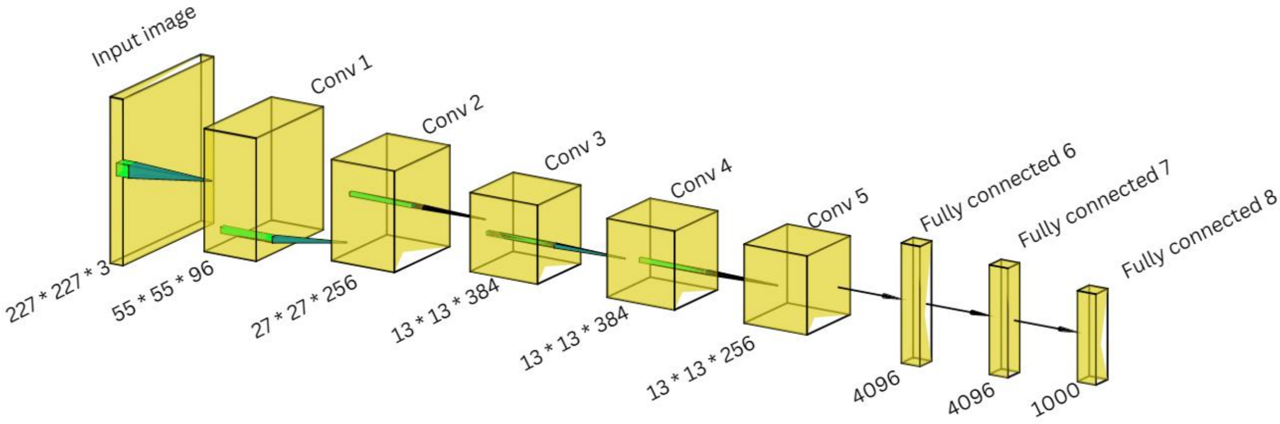

Figure 4: Architecture of AlexNet

For our work we adjusted number of parameters such as epochs, learning rate, dropout, batch size and loss functions. Initially we used 20, 30, 50 and 100 epochs out of which 100 epochs gave an optimum result. For learning rate, we used 0.01,0.001 and 0.1 and we got an optimum result from 0.1 learning rate. When it comes to dropout, we did the same thing and optimum result was provided by 0.1 and batch size was set to 128. We used binary crossentropy as our loss function. Details about our parameters is shown in table 4.

Table 4: Parameters used in model

Parameter
Epochs
Learning Rate
Dropout
Batch size
Loss Function

4.4 Evaluation metrices

For our work we used four metrices to measure our model and they are as follows;

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

Recall $= \frac{TP}{TP+FN}$

F1 Score $= 2 * \frac{P*R}{P+R}$

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

Where TP represents True Positive, FP represents False Positive, TN represents True Negative and FN represents False Negative. Similarly, P, R, represents precision and recall respectively.

V. RESULTS

For this we considered four metrices and they are Accuracy, Recall, Precision and F1 Score but before that to get all values confusion matrix is an import thing to be considered. Fig 5 represents the confusion matrix.

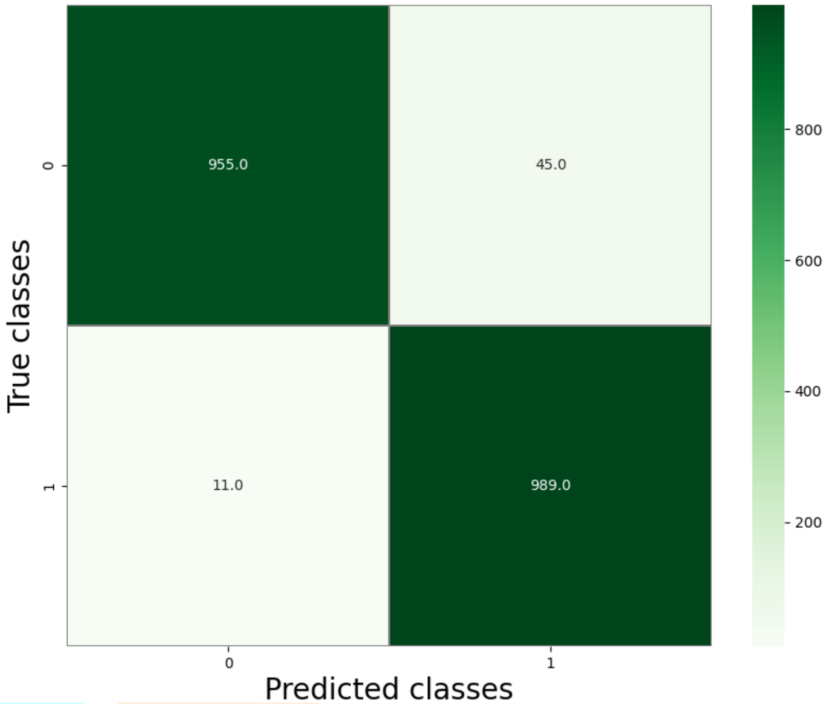

Figure 5: Confusion matrix

As we can see from fig 5 that 955 images were True Negative, 45 were False Negative, 11 were False Positive and 989 were True positive. We tested our model several times where number of parameters were adjusted to get a good result and we have mentioned our optimum parameter values in table 4. After confusion matrix, we used four metrices and we obtained Accuracy of 97.2%, Precision of 98.9%, Recall of 95.64% and F1 Score 97.24% and results are shown in fig 6 and 7.

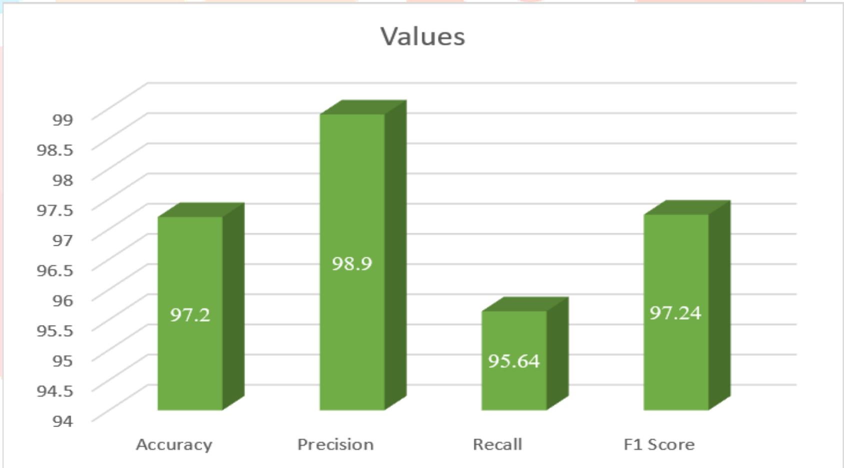

Figure 6: Analysis of AlexNet on the basis of Accuracy, Precision, Recall and F1score

Classes	Accuracy	Precision	Recall	F1 Score
Monkeypox and Acne	97.2%	98.9%	95.64%	97.24%

Figure 7: Result obtained

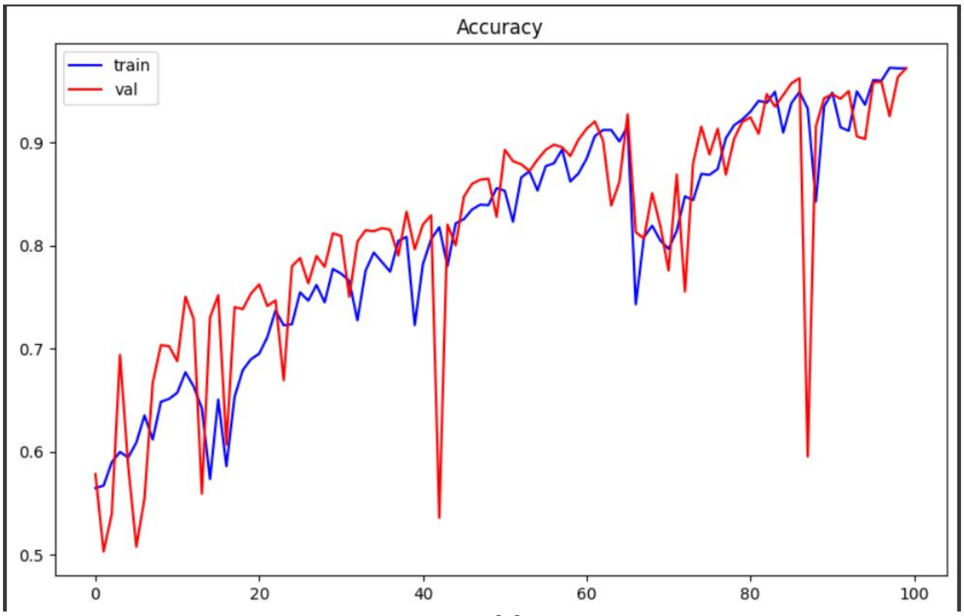

Figure 8: Model accuracy

Figure 6 and 7 represents the accuracy obtained during training and testing of our model where training accuracy is 97.21% and testing accuracy is 97.2% along with that, we have shown predicted output of our model in fig 9.

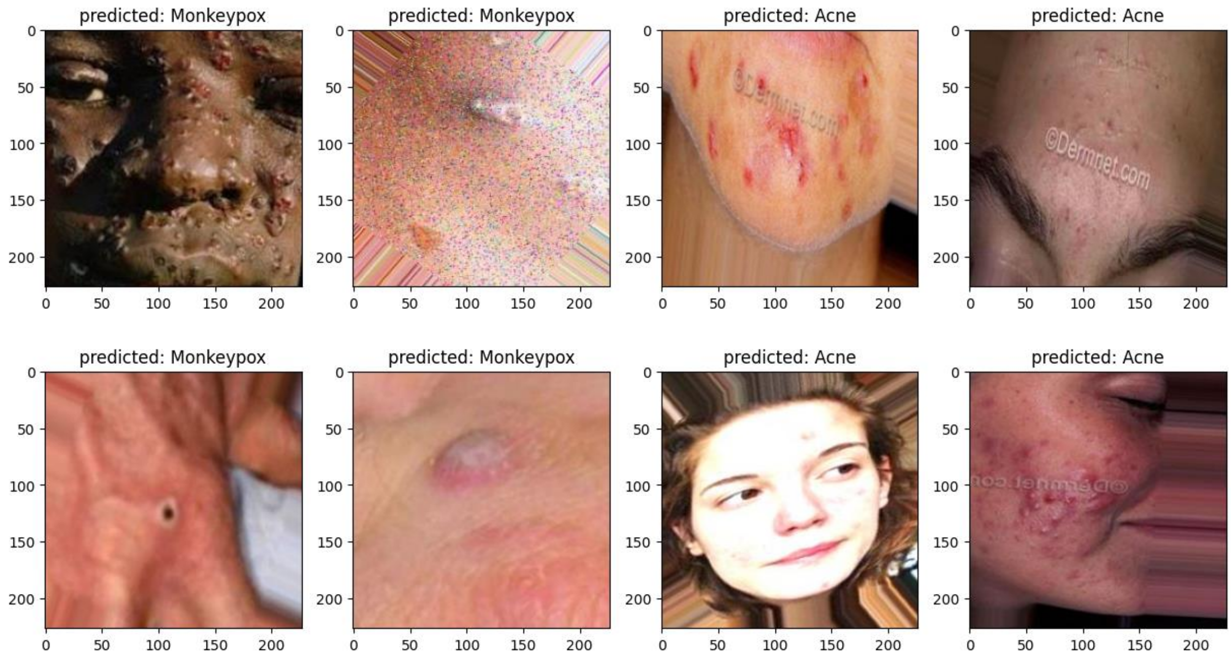

Figure 9: Predicted output

As we can see from figure 9 that model was able to correctly predict the image of respective class with an accuracy of 97.2%.

VI. DISCUSSION AND LIMITATIONS

Since, there are no other research who have considered Acne and Monkeypox, for that we have to make a dataset. There are number of authors who have considered Monkeypox with other non-Monkeypox cases and to collect images of Monkeypox we used a dataset developed by [4]. Their dataset consists of Monkeypox, Chickenpox and Measles skin lesion images out of these we considered Monkeypox real images and used it for our work. For Acne we got 1833 images that was also gathered from Kaggle.

After that, data preprocessing was used to enhance the quality of images that were gathered and augmentation was used, and we end up with 10,000 images of two classes. Images were splitted into training and testing sets in a ratio of 80:20. Our work focuses on binary class classification with each class having images of 5,000 each. We used a deep learning model known as AlexNet in our work. Number of parameters were adjusted and fine-tuned to get a good result. After number of trials and error we got our appropriate values for hyperparameters as shown in table 4. To evaluate our model, we used four metrices as mentioned earlier and results are shown in fig 6, 7, 8 and 9.

Along with that there are some limitations which can be further worked out and they are as follows

- Our work focuses only on binary class classification i.e., we considered only two classes for our work Acne and Monkeypox. Multiclass classification can be considered to get more understanding and to diverse the use of model.
- We considered only one model for our work. To diversify the work more, deep learning models can be used to compare their accuracy and speed along with this model.

VII. 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. Various 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. 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 authors 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.

In this work, we focused on recognizing Monkeypox and Acne skin Lesion images and we achieved an accuracy, precision, recall, training accuracy and F1 Score of 97.2%, 98.9%, 95.64%, 97.21 and 97.24 respectively. For this we used a pre-trained deep learning model known as AlexNet to recognize these diseases. Deep learning specially, CNN is a popular model that is used for image recognition and detection which is backed by number of papers for its accuracy and speed. We believe that our work can help researchers and professionals to get an idea about deep learning model that can be further expanded or refined to detect other diseases.

REFERENCES

[1] C. Sitaula and T. B. Shahi, "Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches" *Journal of Medical Systems*, vol. 46, no. 11, pp. 1-9, 2022, doi. https://doi.org/10.1007/s10916-022-01868-2.

[2] S. A. AlDera and M. T. B. Othman, "A Model for Classification and Diagnosis of Skin Disease using Machine Learning and Image Processing Techniques," *International Journal of Advanced Computer Science and Applications*, vol. 13 ,2022, doi. http://dx.doi.org/10.14569/IJACSA.2022.0130531.

[3] M. M. Ahsan, M. R. Uddin , M. Farjana, A. N. Sakib, K. A. Momin and S. A. Luna, "Image Data collection and implementation of deep learning-based model in detecting Monkeypox disease using modified VGG16," *arXiv e-prints*, 2022.

[4] S. N. Ali, M. T. Ahmed and J. Paul et al," Monkeypox skin lesion detection using deep learning models A feasibility study," *arXiv preprint*, 2022.

[5] M. N. Bajwa et al., "Computer-Aided Diagnosis of Skin Diseases Using Deep Neural Networks," *Applied Sciences*, vol. 10, no. 7, p. 2488, Apr. 2020, doi: 10.3390/app10072488.

[6] T. Shanthi, R. S. Sabeenian and A. R, "Automatic diagnosis of skin diseases using convolution neural network," *Microprocessors and Microsystems*, vol. 76, 2020, doi: https://doi.org/10.1016/j.micpro.2020.103074.

[7] V. R. Allugunti, "A machine learning model for skin disease classification using convolution neural network," *International Journal of Computing, Programming and Database Management*, vol. 3, 2021.

[8] N. Hameed, A. M. Shabut, M. K. Ghosh and M. H. A, "Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques," *Expert Systems with Applications*, vol. 141, 2020.

[9] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," *Sensors*, vol. 21, no. 8, p. 2852, Apr. 2021, doi: 10.3390/s21082852.

[10] M. Altun, H. Gürüler, O. Özkaraca, F. Khan, J. Khan, and Y. Lee, "Monkeypox Detection Using CNN with Transfer Learning," *Sensors*, vol. 23, no. 4, p. 1783, Feb. 2023, doi: 10.3390/s23041783. [Online]. Available: http://dx.doi.org/10.3390/s23041783.

[11] D. Uzun Ozsahin, M. T. Mustapha, B. Uzun, B. Duwa, and I. Ozsahin, "Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesion in Human Subjects Using Deep Learning Framework," *Diagnostics*, vol. 13, no. 2, p. 292, Jan. 2023, doi: 10.3390/diagnostics13020292. [Online]. Available: http://dx.doi.org/10.3390/diagnostics13020292

[12] D. Bala, M. S. Hossain, M. A. Hossain, M. I. Abdullah, M. M. Rahman, B. Manavalan,. N. Gu, M. S. Islam and Z. Huang, "Monkeynet: A robust deep convolutional neural network for monkeypox disease detection and classification," *Neural Networks*, vol. 161, 2023.

[13] M. E. Haque, M. R. Ahmed, R. S. Nila and S. Islam, "Classification of Human Monkeypox Disease Using Deep Learning Models and Attention Mechanisms," 2022 25th International Conference on Computer and Information Technology (ICCIT), pp. 1069-1073, 2022.

[14] S. Wang, B. Kang and J. Ma., et al, "A deep learning algorithm using CT images to screen for Corona virus," *European radiology*, vol. 31, no. 8, 2021.

[15] "Chickenpox Causes Symptoms and Prevention." Cleveland Clinic. Dec. 30, 2021. https://my.clevelandclinic.org/health/diseases/4017-chickenpox (accessed: Dec. 25, 2022)

[16] "Measles Symptoms and causes." Mayo Clinic. May 11, 2022. https://www.mayoclinic.org/diseases-conditions/measles/symptoms-causes/syc-20374857 (accessed: Dec. 25, 2022)

[17] "Melanoma Symptoms and causes." Mayo Clinic. July 18, 2022. https://www.mayoclinic.org/diseases-conditions/melanoma/symptoms-causes/syc-20374884 (accessed: Dec. 25, 2022)

[18] "Ringworm Symptoms and causes." Mayo Clinic. April 26, 2022. https://www.mayoclinic.org/diseases-conditions/ringworm/symptoms-causes/syc-20374884 (accessed: Feb. 25, 2023)

[19] "Acne Symptoms and causes." Mayo Clinic. October 8, 2022. https://www.mayoclinic.org/diseases-conditions/acne/symptoms-causes/syc-20368047 (accessed: Feb. 25, 2023)

[20] A. Roy and M. Lipto, "A Review Paper on Plant Disease Detection and Recognition by Using Deep Learning," *IJRASET*, vol. 10, 2022.

[21] K. Chadaga *et al.*, "Application of Artificial Intelligence Techniques for Monkeypox: A Systematic Review," *Diagnostics*, vol. 13, no. 5, p. 824, Feb. 2023, doi: 10.3390/diagnostics13050824. [Online]. Available: http://dx.doi.org/10.3390/diagnostics13050824.

[22] S. N. Almuayqil, S. Abd El-Ghany, and M. Elmogy, "Computer-Aided Diagnosis for Early Signs of Skin Diseases Using Multi Types Feature Fusion Based on a Hybrid Deep Learning Model," *Electronics*, vol. 11, no. 23, p. 4009, Dec. 2022, doi: 10.3390/electronics11234009. [Online]. Available: http://dx.doi.org/10.3390/electronics11234009

[23] C. V. Naveen, G. Abhiram, V. Aneesh , V. Kakulapati and K. Kumar, "Monkeypox Detection Using Transfer Learning, ResNet50, Alex Net, ResNet18 & Custom CNN Model," *Asian Journal of Advanced Research and Reports*, vol. 17, pp. 7-13, 2023.

[24] T. B. Alakus and M. Baykara, "Comparison of Monkeypox and Wart DNA Sequences with Deep Learning Model," *Applied Sciences*, vol. 12, no. 20, p. 10216, Oct. 2022, doi: 10.3390/app122010216. [Online]. Available: http://dx.doi.org/10.3390/app122010216.

[25] O. Iparraguirre-Villanueva *et al.*, "The Public Health Contribution of Sentiment Analysis of Monkeypox Tweets to Detect Polarities Using the CNN-LSTM Model," *Vaccines*, vol. 11, no. 2, p. 312, Jan. 2023, doi: 10.3390/vaccines11020312. [Online]. Available: http://dx.doi.org/10.3390/vaccines11020312.

[26] K. K. Mohbey, G. Meena, S. Kumar and K. Lokesh, "A CNN-LSTM-based hybrid deep learning approach to detect sentiment polarities on Monkeypox tweets," 2022.

[27] V. Kumar, "Analysis of CNN features with multiple machine learning classifiers in diagnosis of monkepox from digital skin images," *medRxiv*, 2022.

[28] I. Priyadarshini, P. Mohanty, R. Kumar, and D. Taniar, "Monkeypox Outbreak Analysis: An Extensive Study Using Machine Learning Models and Time Series Analysis," *Computers*, vol. 12, no. 2, p. 36, Feb. 2023, doi: 10.3390/computers12020036. [Online]. Available: http://dx.doi.org/10.3390/computers12020036.

[29] M. Patel, M. Surti and M. Adnan, "Artificial intelligence (AI) in Monkeypox infection prevention," *Journal of biomolecular Structure & Dynamics*, 2022.

[30] S. Bengesi, T. Oladunni, R. Olusegun and H. Audu, "A Machine Learning-Sentiment Analysis on Monkeypox Outbreak: An Extensive Dataset to Show the Polarity of Public Opinion From Twitter Tweets," in IEEE Access, vol. 11, pp. 11811-11826, 2023, doi: 10.1109/ACCESS.2023.3242290.

[31] C. Vega, R. Schneider and V. Satagopam, "Analysis: Flawed Datasets of Monkeypox Skin Images," *Journal of medical systems*, vol. 47, no. 1, 2023.

[32] S. Woo, J. Park, J. Y. Lee, and I. S. Kweon, "CBAM: Convolutional Block Attention Module," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11211 LNCS, pp. 3–19, Jul. 2018, doi: 10.48550/arxiv.1807.06521

[33] N. S. A. ALEnezi, "A method of skin disease detection using image processing and Machine learning," *Procedia Computer Science*, vol. 163, no. 1, pp. 85-92, 2019, doi. https://doi.org/10.1016/j.procs.2019.12.090.