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DEEP LEARNING FOR HAZARDOUS CHEMICALS INDUCED SKIN DISEASES CLASSIFICATION: A COMPREHENSIVE ANALYSIS ON INCEPTIONV3 ARCHITECTURE AND MODEL EVALUATION

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Abstract

This research investigates the utilization of deep learning with focus on the InceptionV3 architecture for the categorization of skin conditions induced by contact with hazardous chemicals. The model trained using a carefully curated dataset comprising images of various skin diseases achieves an overall prediction accuracy of 66.67% successfully identifying four out of six evaluated classes. While promising potential practical applications, the analysis reveals a tendency towards over fitting, evidenced by the discrepancy between training and validation accuracies and losses. Future research should focus on mitigating over fitting and expanding the dataset to enhance the model's generalizability and reliability across a diverse range of cases.

Keywords:

Skin Disease Classification, Deep Learning, InceptionV3, Hazardous Chemical, Model Evaluation

1. INTRODUCTION

. In the contemporary healthcare landscape electronic systems such as ECG, the MRI scans and X-rays have become indispensable for disease identification. However, prior to these advanced tools, diagnosing skin conditions involves the identification and assessment of dermatological disorders relied heavily on subjective doctor expertise with errors adversely affecting both patient health and financial well-being. The introduction of image processing techniques revolutionized skin disease detection and marking a paradigm shift.

Everyday household products like detergents, paints and insecticides often contain hazardous chemicals lurking within. These substances such as sodium hypochlorite in bleach to ammonia in furniture polish can wreak havoc on our health. Skin irritation, burns, allergic reactions and even dizziness are just some of the potential consequences of hazardous chemical exposure. While seemingly innocuous, air fresheners and insect repellents can harbor irritating petroleum distillates and pyrethrins causing burning sensations along with respiratory distress. Even seemingly benign alcohol base hand sanitizer products containing ethanol and hydrogen peroxide raises the risk of skin cancer.

Skin diseases due to hazardous chemical exposure severe the health risk with potential temporary or permanent consequences. These chemicals capable of causing harm upon contact and can enter the body and leading to various health issues. Industries and everyday products expose individuals to such chemicals regularly. The core of the COVID-19 pandemic, the popular practice of hand sanitizers as suggested by the World Health Organization (WHO) has sparked alarm due to the alcohol-based nature of these products such as sanitizers containing hazardous chemicals. Prolonged use may result in irritant contact dermatitis and emphasizing the need for a balanced approach to prevent unintended health consequences [1] - [3].

However, the adoption of deep learning techniques in the classification of skin diseases has become a promising and transformative strategy within the field of medical diagnostics. Leveraging convolutional neural networks (CNNs) and sophisticated networks like Inception V3, GoogLeNet and others deep learning module have achieved remarkable success in automating the identification and classification of various skin diseases.

InceptionV3 is a groundbreaking CNN architecture, rose to prominence for its success in the ImageNet Large Scale Visual Recognition Challenge stands out as a prominent competition within the realm of large-scale visual recognition. Its hierarchical structure of convolutional layers allows for the extraction of intricate features from skin images [4], facilitating precise disease classification. Similarly, GoogLeNet with its inception modules and efficient parameter utilization [5], tackles challenges associated with network depth and computational efficiency. These architectures have showcased their ability to discern complex patterns and textures distinctive of various skin conditions [6] [7].

The application of deep learning models for the classification of skin diseases has surpassed conventional diagnostic methods, offering advantages such as speed, scalability and most importantly high accuracy. By training these networks on diverse datasets encompassing various skin conditions and these models acquire the ability to generalize and accurately classify unseen cases.

2. LITERATURE SURVEY

The domain of medical image classification has experienced notable progress through the incorporation of deep learning methodologies. Within deep learning, a subset of machine learning, neural networks with multiple layers are employed to autonomously extract intricate features from medical images. The survey delves into the existing literature concerning diverse deep learning networks applied in the context of medical image classification.

Introduced in 2006, the Deep Learning (DL) approach marked a significant milestone in machine learning development particularly in the realm of hierarchical learning. Its applications expanded into various research domains with a presence in pattern recognition. At its core, deep learning involves hierarchical feature estimation and data representation, encompassing the identification of features from low to high levels. When dealing with image configuration, the conventional machine learning approach falls short, emphasizing the crucial role of input image attributes in feature extraction for impactful outcomes in image processing.

Convolutional Neural Networks for AlexNet, VGG and GoogLeNet have demonstrated remarkable success in classifying medical images. AlexNet introduced by Krizhevsky [8] employs deep convolutional layers to extract hierarchical features. VGGNet [9] emphasizes depth in its architecture, while GoogLeNet [10] introduces inception modules for efficient feature extraction. Residual Networks proposed by He et al. [11] introduced residual connections to address the vanishing gradient problem. ResNets enable the training of extremely deep networks, making them well-suited for complex medical image datasets. RNNs and LSTMs have been applied to medical image sequences such as time based data from patient monitoring. These networks with their capability to capture temporal dependencies are valuable for disease progression prediction and monitoring. Transfer learning, leveraging pre-trained models has gained popularity in medical image classification. Models like ResNet and InceptionV3 pre-trained on large datasets, e.g., for instance, pre-trained models like ImageNet undergo fine-tuning tailored to particular medical imaging objectives [12]. Autoencoders and VAEs are employed for unsupervised learning and feature extraction in medical images. VAEs offer probabilistic interpretations allowing for incertitude estimation in predictions. Ensemble methods, combining predictions from multiple models in the realm of medical image classification have shown enhanced performance in recent times.

Despite notable successes contest persist including interpretability, dataset biases and the need for big datasets. Future directions may involve the integration of explainable AI methodology and the evolution of robust models for specific medical imaging modalities. The reviewed literature underlines the significance of deep learning networks in medical image classification. The choice of a specific network depends on the feature of the medical images and the assignment. Continued research is actively investigating inventive network model and methodologies to enrich the validity of deep learning in the domain of medical imaging. In the domain of medical investigation the collaborative integration of deep learning and shallow learning within artificial neural networks has result in progress in disease prognosis. Magnetic Resonance Imaging (MRI) has proven effective in identifying potential Alzheimer's disease cases. Also the integration of deep learning algorithms into the Optical Coherence Tomography (OCT) system has yielded remarkable results. Traditionally, the evaluation of images involved manual examination for the development of convolutional matrices. Noteworthy initiatives, such as Alam et al.'s [13] automatic system for eczema identification using support vector machines employ segmentation and texture-based feature extraction. The identification of eczema through the application of support vector machines involves the utilization of segmentation and texture-based feature extraction methods to enhance prognosis accuracy. In a study by Immagulate [14], the Support Vector Machine (SVM) was introduced for the analysis of eczema development. In the realm of radiological imaging, both Artificial Neural Networks (ANN) [15] and Convolutional Neural Networks (CNN) [16] play pivotal roles in detection and prognosis. CNN, in particular, has showcased remarkable outputs especially in the realm of skin diagnosis; the adoption of deep learning methodologies has emerged as a notable and innovative approach skin disorder [17].

The skin can suffer adverse consequences from exposure to harmful chemicals, manifesting in a range of skin disorders and conditions as illustrated in Figure 1. Potential outcomes of such exposure encompass skin issues as atopic dermatitis, contact dermatitis, discoid eczema, dyshidrotic eczema, neurodermatitis and seborrheic dermatitis. Atopic dermatitis is regular provocative condition characterized by red and itchy rashes [18] while contact dermatitis manifests as inflammation when the skin comes into contact irritants [19]. Discoid eczema presents as coin-shaped patches of irritated skin [20] and dyshidrotic eczema involves the formation of blisters on the hands and feet [21]. Neurodermatitis is characterized by chronic itching and thickened skin [22], while seborrheic dermatitis affects areas with high oil production and leading to redness and scales [23].

3. METHODOLOGY

In the dynamic landscape of deep learning, the effectiveness of a classification model relies not only on its architectural strategy but also on meticulous data preparation and model evaluation. This study embarks on a comprehensive exploration and beginning with a detailed dataset description that emphasized the careful curation of images into relevant classes. Recognizing the potential limitations of a finite dataset, the incorporation of data augmentation techniques sought to enhance diversity during training. The subsequent focus on image resizing underscored the significance of uniform dimensions for seamless integration into the neural network**.** In this research study, we leveraged a dataset comprising 619 dermatological images sourced from reputable online dermatology resources namely DermNet NZ, DermIS, and Dermnet. The dataset was meticulously curated to ensure diversity in skin conditions encompassing atopic dermatitis, contact dermatitis, discoid eczema, dyshidrotic eczema, neurodermatitis, and seborrheic dermatitis. Our focus in this investigation involved the utilization of 504 images for training purposes and an additional 109 images for model validation. This partitioning allowed us to train our machine learning model on a substantial dataset, fostering the acquisition of intricate patterns and features associated with various dermatological conditions. The reserved set of 109 images for validation played a crucial role in assessing the model's generalization capability and performance on unseen data for dermatological image classification.

Fig.1. Skin Diseases Images

3.1 IMAGE PREPROCESSING

3.1.1 Data Preparation:

The dataset utilized in this study played a pivotal role in shaping the model's learning capabilities and classification accuracy. Comprising a diverse array of images, it was meticulously curated to encompass a broad spectrum of instances relevant to the targeted classification task. The careful curation aimed not only for diversity in the images but also for representativeness, ensuring that each class under consideration was adequately and proportionally represented in the dataset. The careful method employed in creating the dataset established a strong basis for the ensuing training and assessment stages and cultivating a model with the ability to generalize effectively across a diverse range of instances within the specified classes.

3.1.2 Data Augmentation:

To address potential issues related to limited data, data augmentation technique were employed during training. These techniques included random rotations, shearing, zooming and horizontal flipping. The goal was to artificially increase the diversity of the training dataset and promoting better generalization.

3.1.3 Image Resizing:

Entire medical images in the dataset are resized to a uniform size of (229, 229) pixels. This resizing was vital to ensure consistency in input dimensions across all images and allowing them to be fed into the neural network without compatibility issues.

3.2 MODEL ARCHITECTURE

3.2.1 InceptionV3 Base Model:

The choice of the InceptionV3 architecture as the base model for this study was a strategic decision aimed at capitalizing on the extensive knowledge and feature representations acquired by the model during its pre-training on the Image dataset. InceptionV3, developed by Google are renowned for its ability to capture and understand complex visual information through its innovative inception modules. This choice provided a valuable head start for our specific classification task rather than initializing the model from scratch, which could be computationally intensive and require a substantial amount of labeled data, starting with InceptionV3 allowed us to benefit from its pre-existing knowledge. This transfer learning approach enhanced the effectiveness of our model's training process and increased the likelihood of achieving high classification performance on our targeted dataset.

3.2.2 Model Modification:

The modification of the top layers of InceptionV3 aimed to customize the architecture for the specific medical images classification problem for optimizing it for the nuances of the dataset. Here are more details about the adjustments made to the model.

A Global Average Pooling (GAP) Layer was introduced to diminish the spatial dimensions of the feature maps generated by the preceding layers. This layer computes the average value of each feature map, effectively summarizing the information contained in the feature maps. GAP helps in capturing the most salient information from each feature map, promoting computational efficiency and reducing the lot of parameters in the InceptionV3 architecture.

A Dense Layer with ReLU Activation and the GAP layer were added with 256 units. Dense layers are fully connected neural network Layer where each neuron is connected to all neurons in the preceding layer. The utilization of the Rectified Linear Unit (ReLU) as the activation function was employed to introduce non-linearity to the model. ReLU is a commonly used activation function that allows the network to learn complex patterns and relationships within the data. To mitigate the risk concerning over fitting, the incorporation of a dropout layer was introduced with a rate of 0.5. Dropout involves randomly excluding a portion of the neurons maintaining a balance during training is crucial to prevent the model from leaning excessively on particular neurons and promoting better generalization to unseen data. This regularization technique helps to enhance the model's capacity to adapt to novel and unfamiliar instances. The final layer of the modified model consisted of an output layer employing the softmax activation function. The number of units in this layer was modified to align six classes in the dataset. Softmax is commonly used in multi-class classification scenarios; the model transforms its raw predictions into probability distributions across various classes and facilitating the assignment of class labels to input instances. These modifications collectively aimed to the fine-tune InceptionV3 for the unique characteristics of the dataset and enhance its performance in the targeted classification task.

3.2.3 Compilation:

The compilation of the model involved specifying various parameters that dictate how the model should be trained**.** The optimizer chosen for this model was Stochastic Gradient Descent (SGD) stands as a widely employed optimization algorithm within the realm of machine learning that aims to reduce the loss function which is essential for fine-tuning the model parameters during training. It works by updating the weights according to the gradient of the loss function concerning the weights points. The learning rate determines the step size at each iteration during optimization. A learning rate of 0.001 was set to indicate the magnitude of the adjustments made to the model weights. Momentum set to 0.9, introduces a moving average of gradients which helps accelerate SGD in the relevant direction and dampens oscillations. Categorical Cross-Entropy was chosen as the loss function. In multi-class classification problems, where each input belongs to a single class and categorical cross-entropy is a common choice. It assesses the variance between the anticipated probability distribution and the actual distribution of the classes.

Accuracy was selected as the metric to monitor during training. Accuracy is a straightforward metric that count the quantity of accurately categorized the particular class from total image dataset. It contributes a quick and intuitive evaluation of deep learning network architecture. These settings represent a balance between the optimization strategy and the evaluation metric and the aim is to cultivate a model that can generalize adeptly to data which has not encountered during training.

3.2.4 Training:

In the implementation phase of our research, we utilized Python 3.8 as the programming language. Python 3.8 provided a robust and feature-rich environment for developing and executing our machine learning models, offering enhanced capabilities for efficient data processing, algorithm implementation and model evaluation. The training process, spanning 40 epochs involved several key aspects to iteratively improve the model's performance. An epoch refers to a complete pass through the entire training dataset. In this case, the training process was repeated for 40 epochs and each epoch allowed the model to see and learn from the entire dataset. Instead of updating the model's weights after processing the entire dataset (as in traditional batch training), the model's weights were updated after processing smaller batches of data. This approach is known as mini-batch training. Each batch containing a subset of the training data contributions have facilitated weight updates, enabling more frequent adjustments and expediting the convergence process.

The model's weights were updated based on the optimization algorithm (Stochastic Gradient Descent) after processing each batch. The update involves adjusting the weights in the direction that minimizes the loss function, helping the model gradually learn to make more accurate predictions. During the training phase the assessment of model performance involved the scrutiny of diverse metrics and the evaluation of loss values. This monitoring helps identify trends of the evaluation of a model's learning is reflected in its accuracy and loss, serving as indicators to gauge the effectiveness of the learning process, overall performance and adjustments are needed. Continuous monitoring of training progress is crucial for identifying signs of over fitting or poor generalization. Techniques such as early stopping where training is halted, if performance on a validation set ceases, use to improve and may be employed to prevent over fitting. In summary, the training process involved systematically exposing the model to the dataset, updating its weights based on batches of data and monitoring various metrics to ensure effective learning. The use of mini-batches coupled with continuous monitoring contributes to more stable and efficient training, helping the model generalize well to unseen data.

4. RESULT AND DISCUSSION

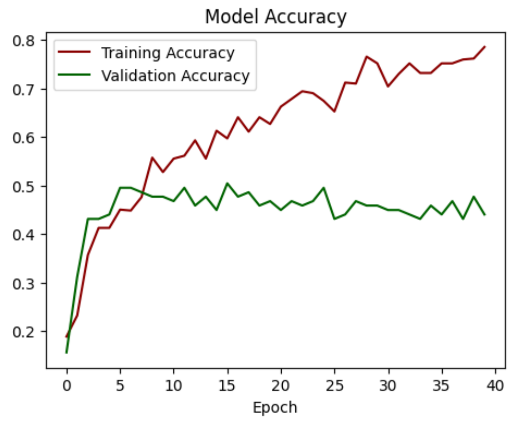
The tracking of the model's performance using training and validation accuracy and loss plots involves several key considerations as explained below.

4.1 TRAINING AND VALIDATION PLOTS

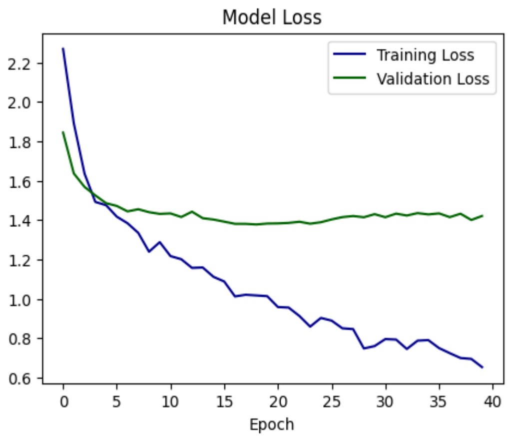
The training accuracy graph depicts the model's progress in learning from the training data across each epoch. It illustrates the percentage of instances correctly classified in the training set. An increasing trend indicates that the model is effectively capturing patterns from the training images. The graph depicting validation accuracy reflects the model's proficiency on an independent dataset that was not employed in the training process. It helps assess demonstrating the model's capacity to extrapolate insights to novel, undisclosed data involves an assessment of both training and validation accuracy. A comparative analysis between the accuracy achieved during the training phase and that observed in the validation phase is crucial in evaluating the model's capability. The training and validation graph reveal insights into potential over fitting when the model memorizes training data without generalizing well. The loss function measures how well the model's predictions align with the actual values. A declining trend demonstrates that the deep learning architecture is minimizing errors during training. Similar to the training loss graph, the validation loss graph shows the model's performance on a separate validation dataset. It helps to analyze model's performance is generalizing to new medical images. An increasing validation loss may indicate over fitting, the model lacks the capability performing well on unseen data. In this particular graph (Fig. 2.), the initial accuracy during training is relatively low but gradually improves over time, reaching a plateau of around 78%. At the outcome, the training accuracy surpasses the validation accuracy over time and latter demonstrates a rising pattern, eventually reaching around 50%. This suggests that the model is learning from the training data, but it may be overfitting to some extent, as the validation accuracy is not quite as high as the training accuracy. The training loss starts off high and decreases over time, reaching a plateau of around 0.6915. The validation loss starts off higher than the training loss but decreases over time, eventually reaching around 1.4723. This implies that the model is acquiring the ability to enhance its predictive potentialities, but it may not be generalizing well to unseen data as the validation set is currently indicating a loss of slightly higher than the loss of training.

4.2 CONVERGENCE ASSESSMENT

Observing the convergence of both accuracy and loss plots is crucial as convergence indicates stability in the learning process. If the recorded values include both the training and validation accuracy stage while the losses reach a minimum, the model has likely learned as much as it can from the available data. The remarkable divergence between training and validation performance or if the validation loss begins to ascend, it may trigger early stopping to prevent over fitting. Early stopping involves halting the training process to avoid a decline in generalization performance.



(a)



(b)

Fig.2. InceptionV3-Accuracy and Loss Plot

An in-depth examination of the training and validation accuracy and loss graphs offers valuable insights into the learning dynamics of the model, its ability to generalize and the possible risks of over fitting. It enables informed decisions during the training process to achieve optimal model performance.

4.3 CONFUSION MATRIX

Examining the model's effectiveness requires a thorough evaluation using a confusion matrix involves a detailed analysis of its classification performance on a dedicated validation set. The confusion matrix represented in a graph that the model's predictions were assessed by comparing them to the real ground truth label. It is particularly useful for multi-class classification problems. Here are more details on the components and interpretation of the confusion matrix. In the realm of medical diagnostics, a true positive (TP) denotes an instance where the model accurately recognizes the presence of a specific skin disease. Conversely, a true negative (TN) occurs when the model correctly determines the absence of a particular skin condition. Within the context of skin disease diagnosis, a false positive (FP) arises when the model erroneously identifies a disease that is not actually present. On the other hand, a false negative (FN) characterizes a scenario where the model fails to detect a skin disease that is genuinely present.

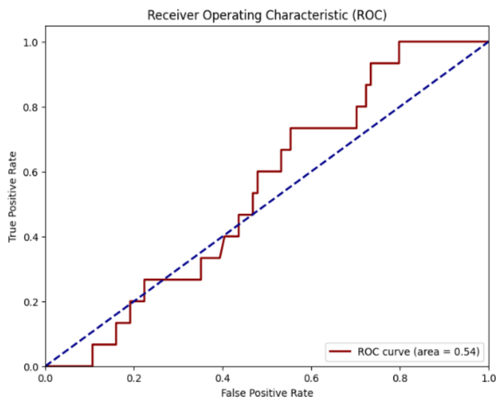


Fig.3. ROC curve (AUC)

The AUC (Area under the Curve) of the Receiver Operating Characteristic (ROC) is a measure that evaluates the effectiveness of a classification model by calculating the area under the ROC curve. It serves as an indicator of the model's performance. An AUC of 1.0 represents a perfect classifier. The ROC curve shown in Fig..3 has an AUC of 0.50. This means that the classifier model is just performing. Nevertheless, it is crucial to emphasize that the AUC is not always a good measure of performance, especially for imbalanced datasets. The ROC curve can employ to assess and contrast the efficacy of various classifiers or to assess the evaluation of a single classifier over time.

4.4 PREPROCESSING

Preprocessing is a crucial step to ensure that new images are compatible with the trained model. The preprocessing steps applied to the six new images involve the technique used during the training and validation phases. The pixel values of the images are likely normalized to a specific range to match the input format of the model. This ensures consistency in data representation and prevents bias in predictions. The new images are resized to the same dimensions used during training (229, 229) pixels.

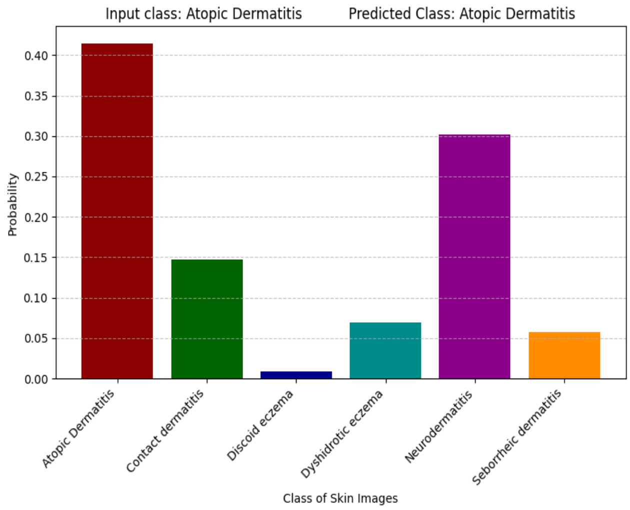


Fig.4.(a) Input Class- Atopic Dermatitis

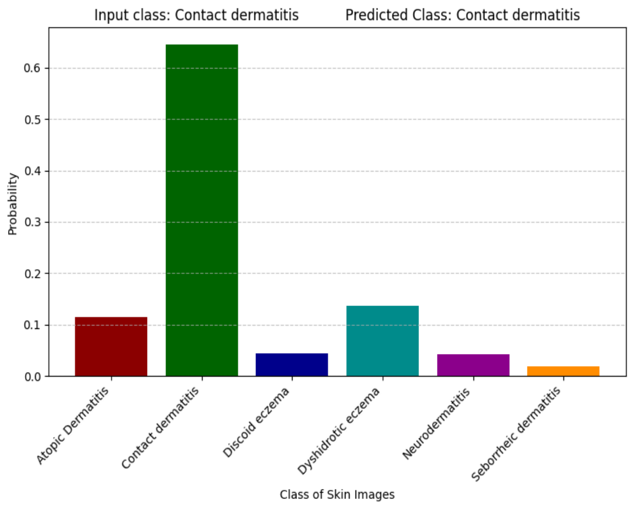


Fig.4.(b) Input Class- Contact Dermatitis

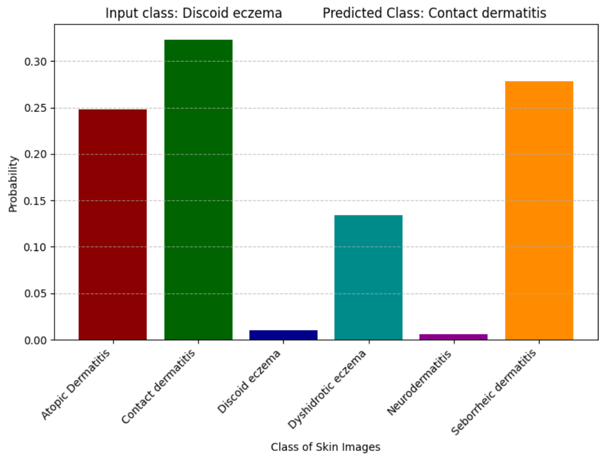


Fig.4.(c) Input Class- Discoid Ecezma

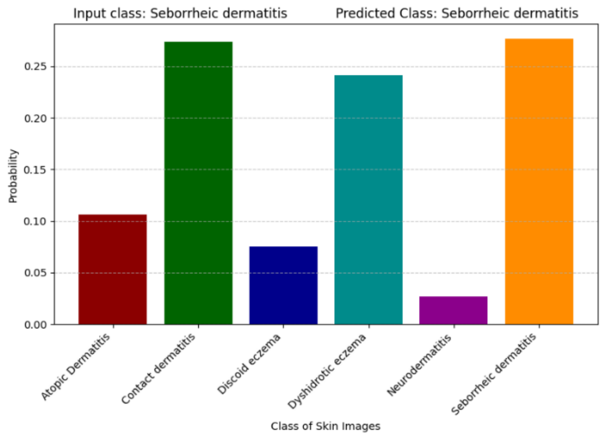


Fig.4.(d) Input Class- Seborrheic Dermatitis

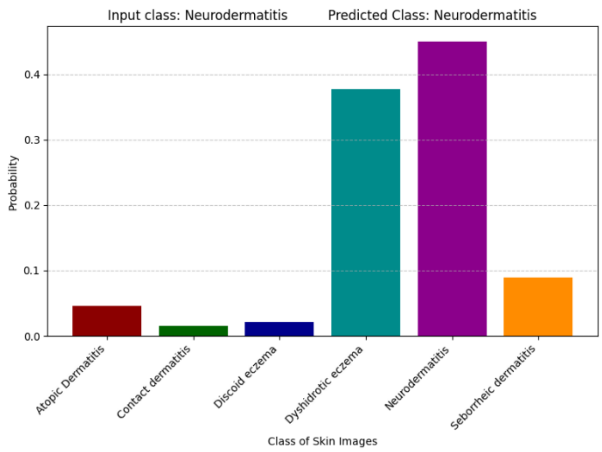


Fig.4.(e) Input Class- Neurodermatitis

This step ensures that the model receives inputs of uniform size, maintaining compatibility. Depending on the augmentation technique used during training such as rotations, shearing, zooming, and flipping, these may be applied to the new images to increases the model's strength to conclusion**.**

4.5 PREDICTION RESULTS

The model predicts class labels for each of the six new images. These predictions provide information on skin disease as the model associates with each image shown in Fig.4. along with the predicted labels and the model outcome probabilities for each class. The probabilities reflect the level of assurance the model has in its predictions as higher probabilities suggest greater confidence. The predictive model exhibited a commendable enhancing the performance of skin disease classification is crucial with an overall prediction accuracy of 66.67%. Out of six classes evaluated as Atopic dermatitis, Contact dermatitis, Discoid, Dyshidrotic eczema, Neurodermatitis and Seborrheic dermatitis, the model correctly identified four classes. Specifically, Atopic dermatitis, Contact dermatitis, Seborrheic dermatitis, and Neurodermatitis were accurately predicted, demonstrating the model's efficacy in distinguishing between these skin conditions.

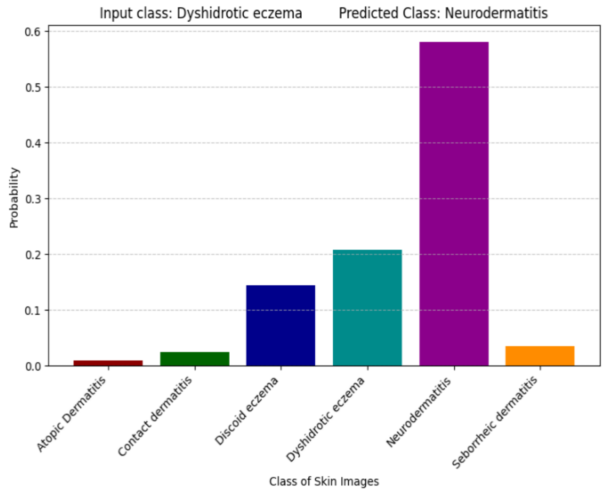


Fig.4.(f) Input Class- Dyshidrotic eczema

Fig.4. Prediction Probabilities and Predicted Class

5. CONCLUSION

The analysis of the enhancing the efficacy of skin disease classification is a key focus in improving performance based on input features reveals both strengths and areas for improvement. The observed trajectory of the training and validation accuracies along with the corresponding losses, suggests that the model undergoes a learning process, achieving a plateau in training accuracy at approximately 78%. However, the validation accuracy, though improving, lags behind at around 50%, indicating a potential degree of over fitting. The decreasing training loss at 2.0 contrasts with the validation loss, which was although decreasing, reaches a slightly higher value of around 2.2. This discrepancy suggests a challenge in generalizing the model to unseen data and prompting the need for further exploration and refinement. In terms of predictive, the model exhibited notable proficiency in accurately classifying skin conditions, showcasing its commendable effectiveness in the field of dermatology, achieving an overall prediction accuracy of 66.67%. Notably, it successfully identified four out of the six evaluated classes as Atopic dermatitis, Contact dermatitis, Seborrheic dermatitis, and Neurodermatitis. The predicted probabilities for each class provided strong confidence levels of the model, with Contact dermatitis exhibiting the highest probability of correct prediction at 64.60%. The findings imply promising utility for practical applications, particularly in aiding dermatologists in the diagnosis and treatment of skin conditions. However, the study acknowledges the necessity of continuous evaluation and refinement to enhance the model's generalization capabilities and ensure its reliability across a broader spectrum of cases. Future research endeavors should focus on addressing the observed over fitting tendencies, potentially through regularization techniques or expanded datasets, fostering a more robust and applicable model in the realm of hazardous chemical affected skin image classification.

6. FUTURE SCOPE

The promising performance of the predictive model in classifying skin diseases opens avenues for future research and development. One crucial aspect of exploration involves investigating strategies to mitigate over fitting and enhance the model's generalization to unseen data. Techniques such as regularization methods or advanced architecture may be explored to address the observed plateau in both training and validation accuracy. Additionally, an in-depth analysis of the model's learning dynamics, particularly during the initial phases of training, could provide insights into optimizing the training process. Further research could focus on expanding the dataset to include a more diverse and comprehensive set of instances for each skin disease class. The inclusion of extra features or the use of advanced data augmentation technique has been upgraded the model's capacity to anticipate tricky patterns and variations in skin conditions. Collaborative efforts between machine learning researchers and medical experts will be instrumental in ensuring the reliability and effectiveness of the model across a broader spectrum of cases and diverse patient populations. This research lays the groundwork for future endeavors geared toward the progressing of the convergence of machine learning and dermatological diagnosis ultimately contributing to improved patient care and outcomes.

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