Convolutional Neural Network for Image-Based Acne and Eczema Classification

Clarence Conde
Computing and Information Technologies
National University Philippines
condec@students.national-u.edu.ph

Celestine Josa Villanueva
Computing and Information Technologies
National University Philippines
villanuevaca@students.national-u.edu.ph

Marchuzs Deimar V. Cortez
Computing and Information Technologies
National University Philippines
cortezmv@students.national-u.edu.ph

Mariel V. Ollage
Computing and Information Technologies
National University Philippines
ollagemv@students.national-u.edu.ph

***Abstract*— Acne and eczema are prevalent skin conditions with significant global impact, particularly in the Philippines where millions suffer. Distinguishing them, especially on facial skin, can be challenging for non-dermatologists, leading to misdiagnosis. This study explores the use of Convolutional Neural Networks (CNNs) for automated classification. A publicly available dataset containing 123 images each of acne and eczema was used. After pre-processing, a CNN model with convolutional, max-pooling, dropout, and dense layers achieved a validation accuracy of 90.62% and test accuracy of 88.89%, demonstrating good generalization. This work suggests the potential of CNNs for improved skin disease diagnosis, particularly relevant in regions like the Philippines with a high prevalence of these conditions, highlighting the need for further exploration with larger datasets.**

Keywords—Convolutional Neural Networks, Image Classification, Acne, Eczema, Deep Learning

I. Introduction

Skin conditions are among the most prevalent health issues globally and come with a heavy cost. The psychological, social, and financial toll that skin diseases have on patients, their families, and society at large is amply included in the multifaceted idea of the burden of skin disease. Some chronic skin diseases such as acne vulgaris and eczema are particularly common, affecting individuals of all ages and ethnicities [1]. This burden is particularly heavy in the Philippines, where common conditions like eczema and acne affect millions of citizens. Eczema, a chronic condition affecting over 12% of the adult population (more than 14 million Filipinos) and 10-20% of infants, highlights the need for accessible tools for early identification [14]. Similarly, acne, the most prevalent skin condition in the Philippines with an estimated 17 million sufferers, underscores the importance of effective solutions [15]. Facial skin is more susceptible to injury than other skin types since it is exposed to the air for a greater portion of the day. Furthermore, people are more concerned with the condition of their facial skin than any other area of their body because it is the most visible aspect of the body [5]. Comedones (open or closed) and inflammatory lesions (papules, pustules, and nodules) are the main lesion forms associated with acne. The typical distribution includes the areas of the face, upper back, chest, and shoulders that are rich in sebaceous glands [2]. While acne typically presents with pimples, blackheads, and whiteheads; eczema can lead to infection, rashes, dry areas, and itching. It's a subtype of dermatitis, a collection of ailments that can irritate or inflame your skin [3]. Despite their distinct characteristics, differentiating between acne and eczema can be challenging especially if they occur on the neck, upper shoulders, or back [13], especially for non-dermatologists, leading to misdiagnosis and delayed treatment. Delayed treatment could be fatal as according to research, those who suffer from severe eczema may also have an increased risk of developing diabetes, high blood pressure, heart disease, stroke, and even visual impairments [12].

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image analysis tasks, achieving remarkable success in various applications like facial recognition and object detection [8]. Their ability to learn hierarchical features directly from image data makes them well-suited for skin disease classification [9]. A CNN architecture typically consists of convolutional layers that extract features from the image, followed by pooling layers that reduce the dimensionality and pooling layers that perform down sampling.

Challenges remain in applying CNNs to skin disease classification. Overfitting due to limited datasets and the difficulty of acquiring large datasets with high-quality labeled images are ongoing concerns. Additionally, the generalizability of the models to unseen data can be an issue.

II. Related Work

Several studies have explored the use of CNNs for skin disease classification. An image-based camel skin diseases classifier proposed a methodology using a Softmax function in the CNN model [1]. Seven experiments was done and the second showed exemplary process as there was no overfitting and the image prediction was correctly labeled. The highest achieved validation accuracy upon solving the overfitting problem was 90.78% validation accuracy and 93.41% training accuracy.

The study for Skin Diseases Diagnosis System used a HAM1000 dataset and found MobileNet with transfer learning to be effective for detecting skin diseases with an accuracy exceeding 85% [10].

"i-Rash" was developed by another study wherein the system utilizes transfer learning with a pre-trained SqueezeNet model that was tested on 1856 images. A cloud-based architecture was used to train the model and deployed on a server. This helped to classify the images in fractions of seconds while overall achieving high accuracy (97.21%), sensitivity (94.42%), and specificity (98.14%) on a non-clinical dataset [11].

In other studies, CNN was not just applied on applications but on medical equipment as well such as Electrocardiograph(ECG). Based on the ECG signal or frequencies, the CNN predicted the apnea syndrome, accuracy, and sensitivity. The study showed a 94% accuracy and 88% sensitivity and showed that this method has a potential as well as advantages of low cost and low complexity. [16]

CNN models can be valuable for identifying less noticeable diseases or providing a more objective assessment [10]. Integrating CNNs with mobile apps or medical equipment offers a convenient and accessible approach for early diseases detection.

III. METHODOLOGY

The dataset used in this research was outsourced. The programming, analysis, and visualization of this research were done using Python as the programming language on Google Colab.

A. Data Acquisition

Figure 1: Data Sample for Acne and Eczema Dataset

A publicly available dataset containing labeled skin images for acne and eczema was obtained from Kaggle. This dataset will serve as the foundation for training and evaluating the proposed CNN model. This dataset contains 123 images of eczema and 123 images of acne. It was divided into three sets:

- Validation Set: 16 images of eczema, 16 images of acne.
- Training Set: 89 images of eczema, 89 images of acne.
- Testing Set: 18 images of eczema, 18 images of acne.

These sets ensure that the model is trained, validated, and tested on distinct images to evaluate its performance accurately.

B. Data Pre-processing & Cleaning

Before feeding the images into the CNN model, the dataset needed to be pre-processed and cleaned to ensure the model's performance is optimized. The key steps involved in this process are:

Removing Duplicates: Duplicate images can lead to overfitting, where the model performs well on the training data but poorly on new, unseen data. By removing duplicates, we ensure the model learns to generalize better.

Rescaling: The pixel values of the images are rescaled to a range of [0, 1]. This normalization step helps the model train faster and achieve better performance. This is done using the Rescaling(1./255) layer in the CNN model, which scales pixel values from [0, 255] to [0, 1].

C. Convolutional Neural Networks (CNN) Model

The CNN model is designed to effectively classify images into acne or eczema categories. The use of convolutional layers extracts relevant features, max-pooling reduces dimensionality, dropout layers prevent overfitting, and dense layers perform the final classification. The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss to ensure efficient training. Early stopping was used to monitor the validation loss and stop training when no further improvements are observed, preventing overfitting.

The model employs a sequential approach with multiple layers to prevent overfitting and extract complex features. First, is to rescale the layer to normalize the pixel values, followed by a Conv2D layer with 32 filters and ReLU activation to capture initial features. Followed by MaxPooling2D layer to reduce spatial dimensions, and a Dropout layer with a rate of 0.2 that helps to prevent overfitting. This pattern is repeated until the 4th layer with the Conv2D layer having variations of 64, 128, and 128 simultaneously for each layer. The output is then flattened by a Flatten layer to be fed into a fully connected Dense layer with 128 neurons and ReLU activation, followed by a dropout layer with a rate of 0.5. Lastly a Dense output layer with 2 neurons was used to provide the model's predictions.

D. Training

The model trained through 30 epochs with an early callback when the validation training started to decline and validation loss stopped improving, preserving the best model weights. This prevents the model from continuing the training despite having 30 epochs that were set.

E. Visualization

Linear graph was used to plot the training and validation accuracy and loss over epochs to visualize the model's learning process. The confusion matrix was used as well to evaluate the performance of the classification model on the test dataset. This shows the numbers of both correct and incorrect classified images of acne and eczema.

IV. RESULTS AND DISCUSSION

```
Final Validation Accuracy: 0.7812
2/2 [==============================] - 0s 17ms/step - loss: 0.4066 - accuracy: 0.8333
Test Accuracy: 0.8333, Test Loss: 0.4066
```

```
Final Validation Accuracy: 0.9062
2/2 [==============================] - 0s 11ms/step - loss: 0.2944 - accuracy: 0.8889
Test Accuracy: 0.8889, Test Loss: 0.2944
```

Figure 2: Final Validation Accuracy Snippet

CNN model was evaluated by its capability to accurately identify the image whether it is Psoriasis or Acne. It achieved a validation accuracy of 78% to 90%. The variation in accuracy was expected as the model trains the dataset randomly. It is shown in figure 4 that despite a lower validation accuracy, the test accuracy was higher where the validation accuracy is 78.12% and the test accuracy is 83.33%. The consistently higher test accuracy compared to validation accuracy suggests a possible overfitting. This could be because the test set has a similar distribution to the training set, allowing the model to perform well on unseen examples that closely resemble the training data even though this is not the same case for other runs. It can be observed that for the 90.62% validation accuracy that the test accuracy is 88.89%. It is shown in figure 3 that both the train and validation accuracy increased and for the loss, overall it continued to both decline.

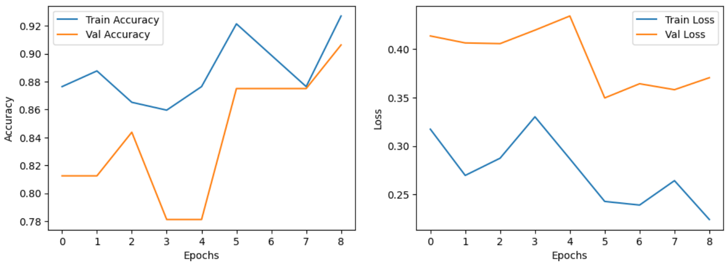

Figure 3:90.62% Accuracy & Loss VS Epoch

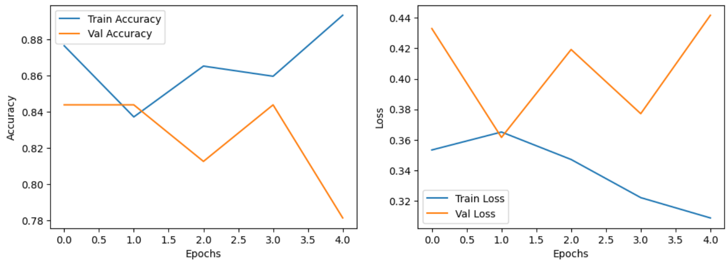

Figure 4: 78.12% Accuracy & Loss VS Epoch

Focusing on the highest validation accuracy run, 90.62%, figure 5 shows the confusion matrix and provides a clearer visualization of its performance. Out of 18 images from the test set, 15 out of 18 were correctly classified under the acne class and a higher success rate for eczema with 17 out of 18 classified images. This indicates a high level of accuracy in distinguishing between acne and eczema, with a minor number of misclassifications.

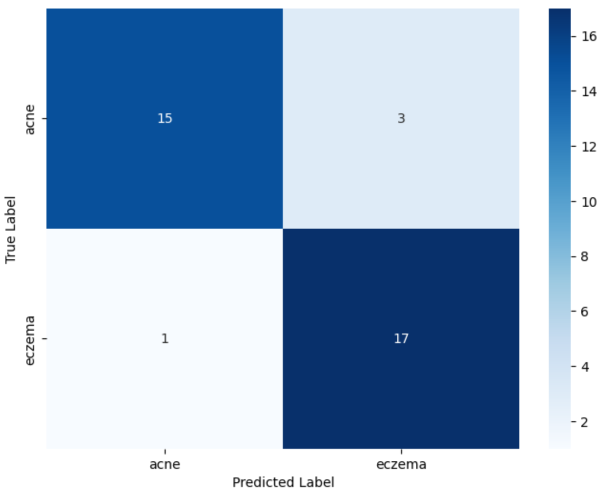

Figure 5: 90.62% Confusion Matrix

	precision	recall	f1-score	support
acne	0.94	0.83	0.88	18
eczema	0.85	0.94	0.89	18
accuracy			0.89	36
macro avg	0.89	0.89	0.89	36
weighted avg	0.89	0.89	0.89	36

Figure 6: 90.62% Classification Report

For Further analyzing the model's performance figure 6 shows the classification report. There were 18 data points or support for this test set. The precision shows the accuracy of the model per class. The model correctly classified 94% of acne data points and 85% for eczema. A high recall signifies that the model doesn't miss relevant data points. There are 83% and 94% of instances for acne and eczema simultaneously. The F1-score indicates that the model is performing well for both precision and acne. The model scored 88% and 89% which indicates the model's effectiveness for both aspects. Overall, this is considerably high and showed the capability of the model to be able to classify the acne and eczema.

V. CONCLUSION

In conclusion, the CNN model achieved a promising performance and accuracy that ranges from 78 to 90%. Variation of accuracy for each run is to be expected due to the randomness of the training data selection. For runs that had a higher test accuracy than validation accuracy is a sign of potential overfitting.

Further optimization and addition of various techniques and broadening of the dataset can address the overfitting issue and could further improve the accuracy of the model.

REFERENCES

[1] M. K. A. Basra and M. Shahrukh, "Burden of skin diseases," Expert Review of Pharmacoeconomics & Outcomes Research, vol. 9, no. 3, pp. 271–283, Jun. 2009, doi: 10.1586/erp.09.23.

[2] A. L. Zaenglein, "Acne vulgaris," New England Journal of Medicine/˜ the œNew England Journal of Medicine, vol. 379, no. 14, pp. 1343–1352, Oct. 2018, doi: 10.1056/nejmcp1702493.

[3] "Eczema: symptoms, causes, and treatment," WebMD, May 29, 2024. https://www.webmd.com/skin-problems-and-treatments/eczema/atopic-dermatitis-eczemafpso

[4] S. Inthiyaz et al., "Skin disease detection using deep learning," Advances in Engineering Software, vol. 175, p. 103361, Jan. 2023, doi: 10.1016/j.advengsoft.2022.103361.

[5] "Studies on different CNN algorithms for face skin disease classification based on clinical images," IEEE Journals & Magazine | IEEE Xplore, 2019. https://ieeexplore.ieee.org/abstract/document/8720210

[6] "A Survey of Convolutional Neural Networks: Analysis, applications, and Prospects," IEEE Journals & Magazine | IEEE Xplore, Dec. 01, 2022. https://ieeexplore.ieee.org/abstract/document/9451544

[7] "CURETO: Skin Diseases Detection using Image Processing and CNN," IEEE Conference Publication | IEEE Xplore, Nov. 17, 2020. https://ieeexplore.ieee.org/abstract/document/9299041

[8] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[9] M. Michalska, "SELECTED APPLICATIONS OF DEEP NEURAL NETWORKS IN SKIN LESION DIAGNOSTIC," Informatyka, Automatyka, Pomiary W Gospodarce I Ochronie Środowiska, vol. 11, no. 4, pp. 18–21, Dec. 2021, doi: 10.35784/iapgos.2804.

[10] M. Maduranga and D. Nandasena, "Mobile-Based Skin Disease Diagnosis System using Convolutional Neural Networks (CNN)," International Journal of Image, Graphics and Signal Processing, vol. 14, no. 3, pp. 47–57, Jun. 2022, doi: 10.5815/ijigsp.2022.03.05.

[11] N. Hameed, A. Shabut, F. Hameed, S. Cirstea, S. Harriet, and A. Hossain, "Mobile based Skin Lesions Classification Using Convolution Neural Network," Apr. 01, 2020. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3760249

[12] Key, A. P. (2024, March 12). Complications of severe eczema. WebMD. https://www.webmd.com/skin-problems-and-treatments/eczema/complications-severe-eczema

[13] Dpt, K. G. P. (2024, May 27). Eczema vs. Acne: How to Tell the Difference. Verywell Health. https://www.verywellhealth.com/eczema-and-acne-

5200263#:~:text=Eczema%20and%20acne%20both%20cause,%2C%20which%20acne%20doesn't.

[14] Dermatolgy. (n.d.). Eczema. Dermatology. https://dermatology.ph/dermatology-conditions/eczema/

[15] Acne — Skin MD - dermatologist in Ortigas, Pasig. (n.d.-b). Skin MD - Dermatologist in Ortigas, Pasig. https://www.skinmd.ph/conditions/acne

[16] Detection of sleep apnea syndrome by CNN based on ECG. (n.d.-a). https://iopscience.iop.org/article/10.1088/1742-6596/1757/1/012043/pdf