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Skin Lesion Classification Using Deep Learning

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Abstract: Skin lesion is one of the most common types of cancer globally, and early recognition is essential for a better prognosis for patients. In this paper, we built a machine learning-based image classification system to classify dermoscopic skin lesion images into a range of diseases. We adopted the publicly available HAM10000 dataset and preprocessed it for model optimization and the prevention of overfitting, including image resizing, normalization, and data augmentation. We also investigated class distribution to see the data imbalance and give a hint for model training. To demonstrate the classification ability, we conducted the experiment with four models, including SVM, CNN, VGG16, and ResNet50.The SVM achieved an accuracy of approximately 80%, while the CNN improved this to 92%. The VGG16 model further increased the accuracy to 94%. ResNet50 outperformed all other models, achieving the highest accuracy of 95%. Our results demonstrate that deep learning models, particularly ResNet50 and VGG16, are highly effective in skin lesion classification and have significant potential for supporting early skin cancer diagnosis and aiding healthcare professionals in clinical decision-making.
Keywords: CNN, VGG, ResNet, Deep Learning, OpenCV.

I. INTRODUCTION

Skin lesion cancer is one of the most prevalent diseases and a leading cause of death worldwide. Early diagnosis is very vital, as it enhances the possibility of the victim in getting treated and recovering. But manual diagnosis from doctors takes time, and could be inconsistent based on the doctors' experience and observation. Computer systems using AI and Deep Learning have been an aid in addressing this problem. Such systems can automatically analyze skin images and classify various skin lesions with accuracy, assisting doctors in more rapid and reliable diagnoses.

In this paper, we used the HAM10000 dataset, which consists of skin lesion images. We preprocessed, labeled, and visualized the data before training our model. We then trained the models and compared 4 models, including SVM, CNN, ResNet50, and VGG16. We hope to find the best accurate model for the task of skin lesion classification by comparing their performance. Our work demonstrates how AI can aid in early and accurate skin disease diagnosis.

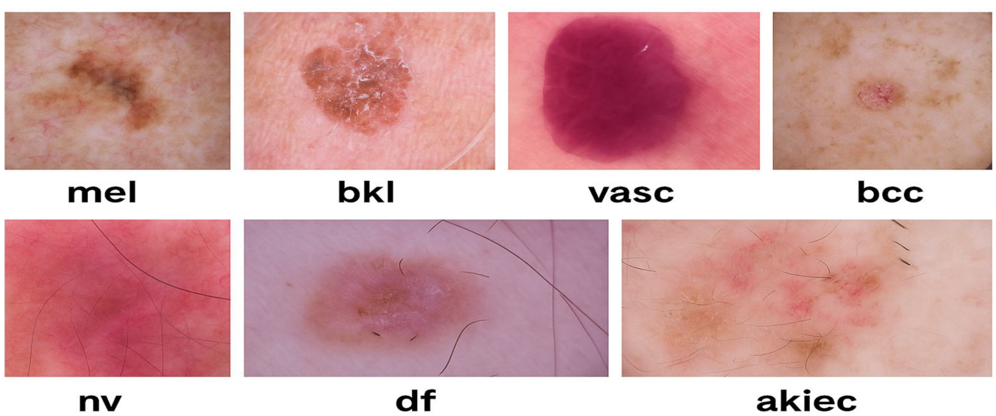

Fig1. Skin lesion Classification Images

Objectives:

1. To develop a system that can automatically classify skin lesion images into different diseases classes using machine learning and deep learning techniques.
2. To compare the performance of multiple models (SVM, CNN, VGG16, and ResNet50) and identify the most accurate model for skin lesion detection.
3. To support early diagnosis of skin cancer by providing a reliable and efficient image classification tool for doctors and individuals.

II. LITERATURE SURVEY

Many methods have been introduced by various researchers to classify skin diseases. Related works are classified into various types according to data sets, feature extraction approach, feature selection approach, and classification method. This subsection reviewed the prostrated articles for the tools and procedure used in the previous studies and research gaps.

A. *Overview of Existing Work*

Skin lesion detection based on dermoscopic images has received considerable attention in the recent past. Classical machine learning models, such as Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN), were primarily applied with manually designed features such as color, shape, and texture. But these models performed poorly under high variation of skin lesions. After the rise of deep learning, Convolutional Neural Networks (CNNs) were the de facto standard. Convolutional Neural Networks (CNNs) extract relevant features automatically from raw images, and higher accuracy is obtained after classification. Previous studies adopted pretrained models such as VGG16, InceptionV3, and ResNet50 by using transfer learning, which can enhance performance with a small amount of medical images. Public datasets such as HAM10000 have been extensively used for training and testing.

B. *Challenges in Current Solutions*

In spite of such achievements of deep learning models in categorizing skin lesions, there are many challenges ahead. One of the significant problems is class unbalance, which refers to the skewness in the number of samples in datasets of various skin lesions, causing the models to predict incorrectly. Moreover, the appearance similarity of the lesions of different subtypes is challenging for the model to distinguish. High computing overhead Deep learning models also have high computational costs, which may prevent them from being used for real-time or mobile applications. These models are also difficult for clinicians to interpret, and as a result, are hard to use with confidence in a clinical decision-making setting.

III. METHODOLOGY

In our experiments, we analyzed the HAM10000 dataset, which is one of the most popular benchmark datasets in skin lesion classification. To get the data ready for model training, we did some preprocessing steps such as image-scale-normalization and data-augmentation, to help the model train better with less overfit.

A. *Dataset Collection*

The HAM10000 (Human Against Machine with 10000 training images) dataset contains 10,015 dermatoscopic images of pigmented skin lesions from seven different classes:

- Melanocytic nevi (nv)
- Melanoma (mel)
- Benign keratosis-like lesions (bkl)
- Basal cell carcinoma (bcc)
- Actinic keratoses (akiec)
- Vascular lesions (vasc)
- Dermatofibroma (df)

Feature	Explanation	Measurement	Range / Values
image_id	Unique ID for each dermatoscopic image	Text (String)	Unique alphanumeric string
lesion_id	ID for the lesion (can be same for multiple img)	Text (String)	Alphanumeric
dx	Diagnosis of the lesion (7 disease types)	Categorical	['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc']
dx_type	Method of diagnosis	Categorical	['histo', 'follow_up', 'consensus', 'confocal']
age	Age of patient	Integer (Years)	0 – 100+
sex	Sex of patient	Categorical	['male', 'female'] (can be null)
localization	Location of the lesion on the body	Categorical	['back', 'lower extremity', 'abdomen'...]
dataset	Dataset name (constant)	Text (String)	"HAM10000"
target_label	Encoded label for 0–6 classification (e.g. 0 to 6)	Integer (0–6)	0: akiec, 1: bcc, ... 6: vasc

Table 1: Dataset Information

The metadata available in the dataset includes age, sex, and anatomical site, which can be beneficial for multi-modal approaches in the future. All images are in RGB color space and at various resolutions and have been acquired from diverse subjects and imaging apparatuses.

B. *Data Preprocessing*

- Data Augmentation:
  Due to class imbalance (some classes had very few images), data augmentation was applied to increase diversity and enhance model generalization. Augmentation such as rotation (±20°), zoom (20%), shift (20%), and horizontal flip was performed using Keras' ImageDataGenerator. This added more data points to the dataset, reducing overfitting.
- Image Resizing and Normalization:
  All images were resized to 224x224 pixels to be at a standard input size and to make processing more efficient. The dimensions were resized to increase the speed of the training process, and important features of the image were preserved. Afterward, the pixels were normalized to a value range between 0 and 1 to facilitate model learning.
- Label Encoding and One-Hot Representation:
  The original textual class labels (for example, "melanoma") were encoded as numbers using label encoders. These numerical labels were also converted into one-hot vectors. This encoding was necessary to train classification models as Convolutional Neural Network (CNN) and Support Vector Machine (SVM), which require numerical inputs.

C. *System Architecture*

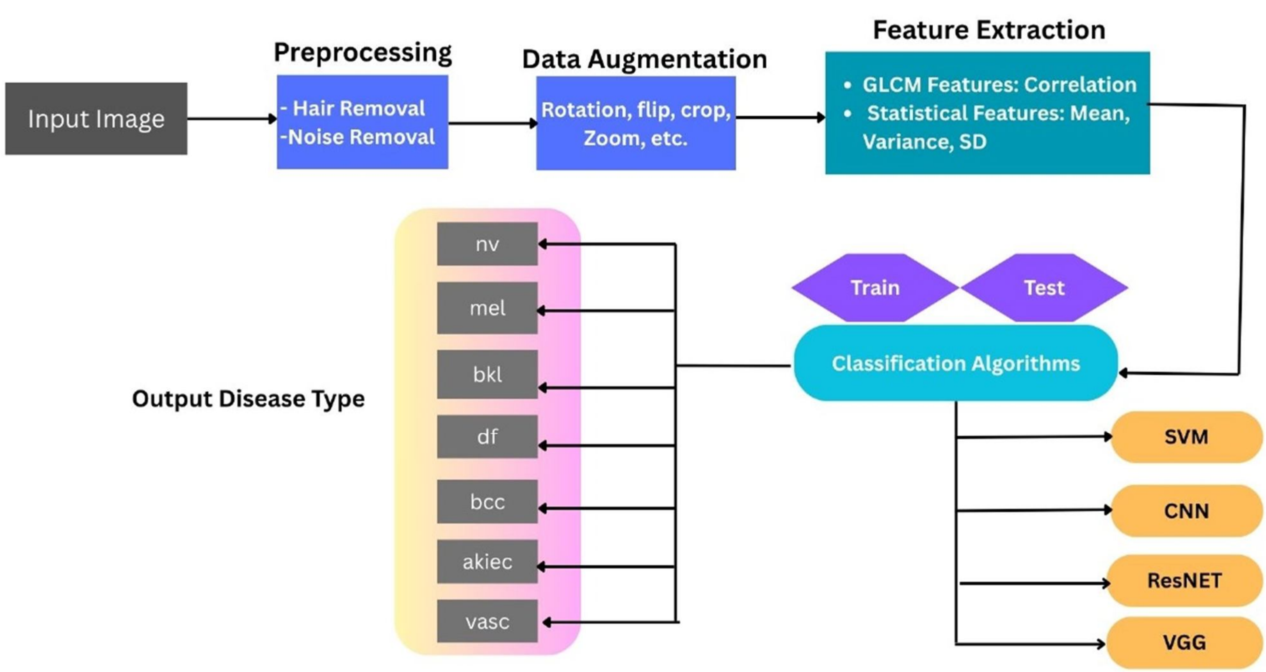

Fig 2. System Architecture

1. Skin lesion classification Dataset is the input; the dataset is divided into 80%(training) and 20% (test).
2. The test and train set is used to test the final model trained on the training data.
3. The Trained model's performance is evaluated using the test data.
4. This step includes matrices like accuracy, precision, recall, F1-score, etc.

D. Models

- Convolutional Neural Network (CNN)

CNNs are a class of deep neural networks designed to recognize patterns directly from image data. They can automatically discover edges, shapes, and textures with small filters. A simple CNN has three types of layers: the convolutional layers (as feature extractors), the pooling layers (for reducing the size of the data), and the fully connected layers (for the classification of the image). CNNs have been successfully applied to real-world applications such as face recognition and medical image analysis. This makes them suitable for our project because they can learn purely from raw images and are good with large, very detailed dataset which will be more accurate for skin lesion classification.

- ResNet

ResNet (Residual Network) is one of the most advanced models in deep learning that enables solving the problem that accuracy will be worse in very deep networks. It employs skip connections or residual blocks, which permit the model to 'skip' certain layers, working towards better and faster learning. Because it is able to train a very deep network without accuracy degradation, ResNet is very powerful for image classification tasks. In our work, we adopted ResNet50 (50 layers) as a well-known architecture that can achieve satisfactory performance on complicated images. Its ability to learn deep features makes it ideal for classifying different types of skin lesions with high accuracy.

- VGG16

VGG16 can serve as a representative deep-learning model composed of a deep, simple, and uniform architecture with 16 layers. It is largely made up of stacked 3x3 convolutional filters, max pooling, and fully connected layers at the end for classification. VGG16 is popular for its simplicity and high performance in image classification. We used it in our project because it’s good for transfer learning. our idea is to use a pre-trained model and re-train it to deal with skin lesion classification. VGG16 made it possible to obtain excellent accuracy when used to classify images by being simple to implement and understand.

IV. EXPERIMENTAL RESULTS AND MODEL COMPARISON

In this section, we introduce and compare the performances of four classification models: CNN, ResNet50, VGG16, and SVM. Evaluation was performed against the validation set using common metrics: accuracy, precision, recall, and F1-score. We also present findings that we believe share new insights into the strengths and limitations of how these seven different skin lesion types were themselves modelled.

A. Convolutional Neural Network (CNN)

The CNN was taught from the very beginning, and 40 training runs were performed with the Adam optimiser, an initial learning rate of 0.0005. A learning rate scheduler (ReduceLROnPlateau) decreased the learning rate by a dynamic factor if the validation loss didn’t decrease, to speed up convergence. The final model had a training accuracy of 93.05%, a validation accuracy of 93.03%, and a validation loss is 0.1923. The CNN demonstrated high generalization across overall classes, with the model especially performing well for Dermatofibroma (df) and Vascular lesions (vasc). We observed that a few misclassifications were made between visually similar classes, such as mel and bkl. As expected, the confusion matrix shows that the majority of the predictions were on the diagonals, suggesting good overall classification performance. The accuracy and loss plots display smooth convergence, indicating the stability and effectiveness of the model.

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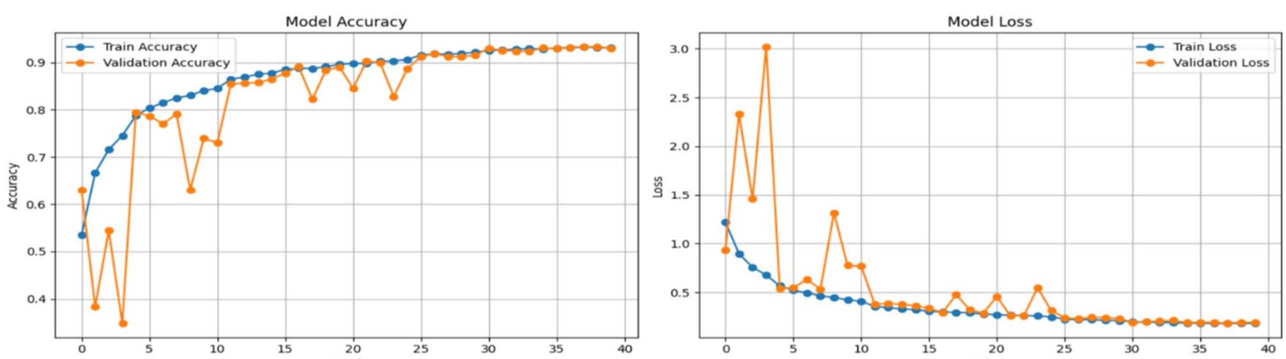


Fig 3. CNN Model Accuracy and Loss Curves

B. ResNet50 (Transfer Learning)

A transfer learning approach was used with ResNet50, with the pre-trained weights obtained from ImageNet. Training was performed in two steps; first, the pretrained base layers were frozen and only the customized top layers were trained for 10 epochs. In the second stage, we fine-tuned the complete model end-to-end for 10 epochs with a small learning rate of 1e-5.

The best performing model is the ResNet50, which consists of training accuracy of 97.56% and testing accuracy of 95.53% with a lowest validation loss of 0.1399. The Residual connections in ResNet facilitated fast gradient flow and learning deeper features specific to the skin lesion classification.

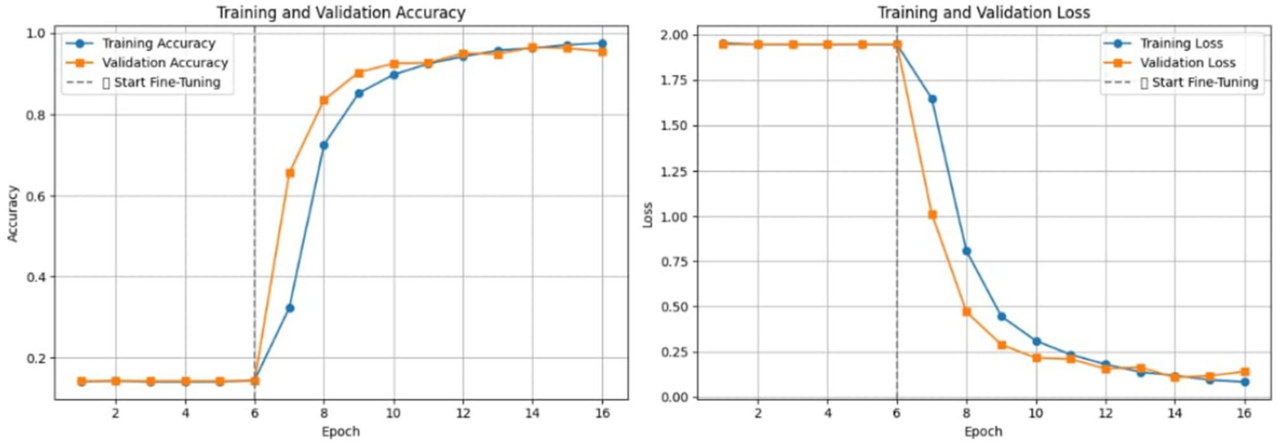


Fig 4. ResNet50 Model Accuracy and Loss Curves

Support Vector Machine (SVM): SVM was realized based on the deep features extracted from the last fully connected layer of the trained CNN. When first tested on features of a frozen CNN, the model showed only 14% accuracy. After feature extraction from the pre-trained CNN model, the SVM performed better with a validation accuracy of 79.90 and log loss of 0.5593.

C. VGG16 (Transfer Learning)

The VGG16 model was applied in conjunction with transfer learning by loading the pre-trained weights of ImageNet. Training occurs in two stages; for the first stage, the base model is frozen and only the custom top layers are trained for 10 epochs. Subsequently, fine-tuned the whole model with a low learning rate,1e-5, for 10 epochs.

The training accuracy of the model was 91.63% and validation accuracy was 94.59% (validation loss: 0.1490). Performance of VGG16 was quite good across all classes. It achieved similar, very high accuracy in distinguishing relatively common types of lesions (melanocytic nevi, vascular lesions) and, to a lesser extent, more challenging classes (e.g. melanoma, benign keratosis-like lesions).

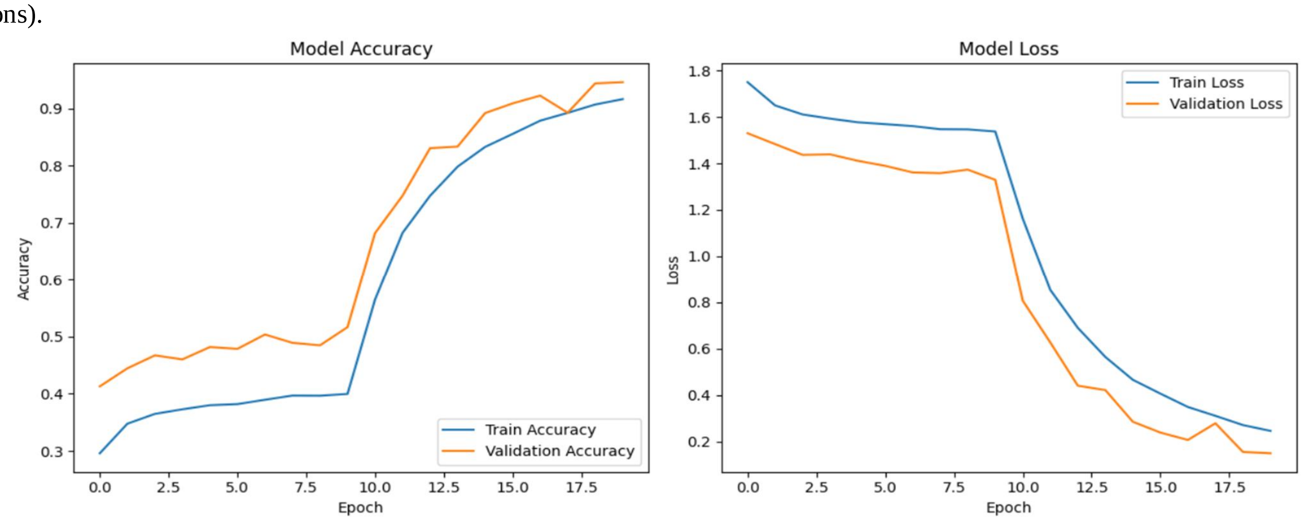


Fig 4. VGG16 Model Accuracy And Loss Curves

D. Model Prediction

We have employed the trained models to classify dermoscopic images based on the type of skin lesion displayed in the images. In each model, the image is processed by identifying key features and the model will classify the lesion into one of several defined categories. Below is an example of how the model uses visual characteristics to detect and classify a skin lesion. This prediction can assist doctors with early diagnosis and treatment planning.

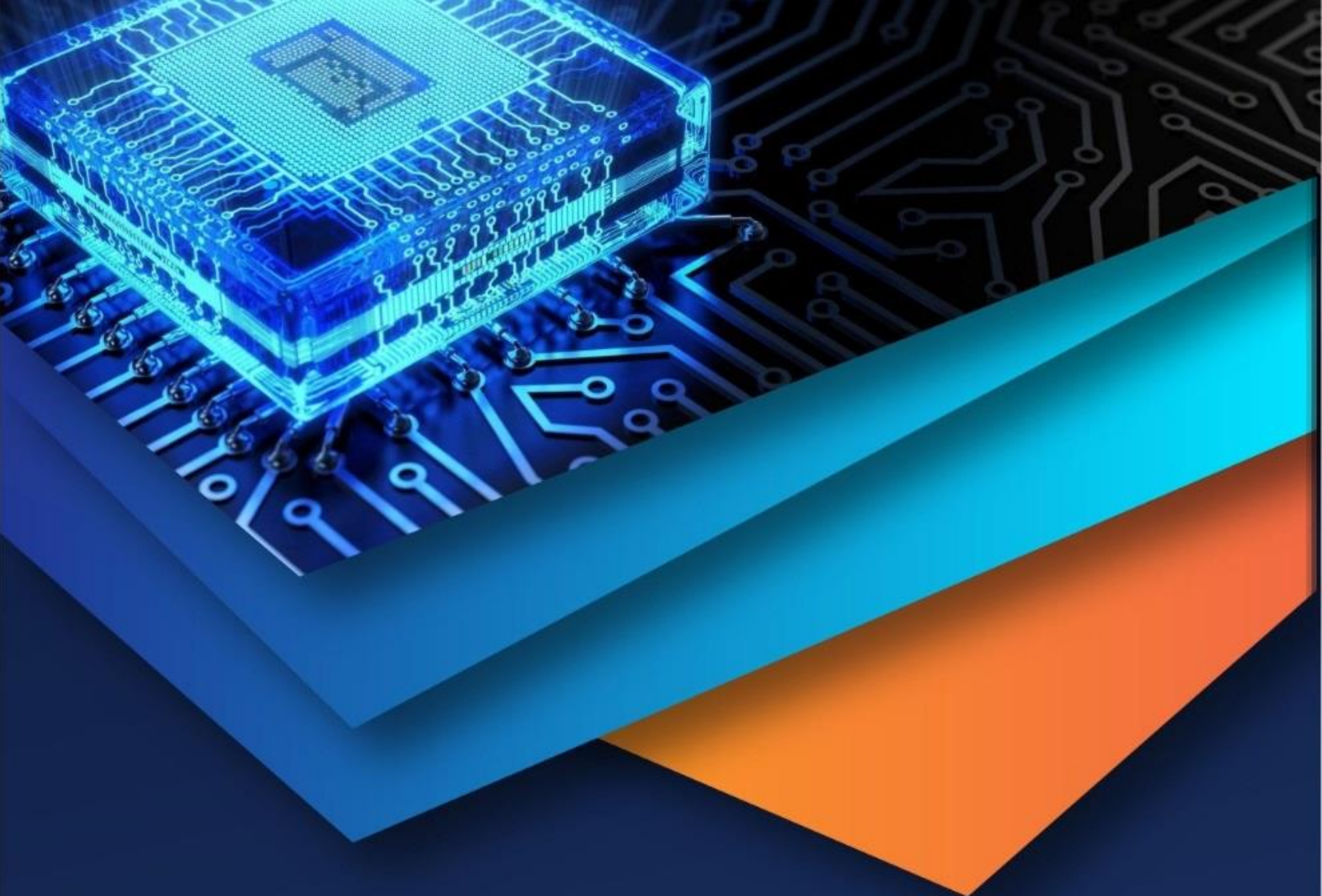
Fig 5. Prediction

V. CONCLUSION

This paper demonstrates the use of machine learning and deep learning models with great success for automatic classification of skin lesions. To leverage the HAM10000 dataset and appropriately preprocess the data including addressing data imbalances and the use of different training strategies, we have been successful in optimizing the use of the models for training. The models performed similarly to one another in various ways: SVM typically gave us baseline performance, however, CNN and VGG16 showed noteworthy improvements. ResNet50 achieved the highest accuracy, which suggests its superior ability to extract features, generalization to unseen data, and model regularization. Therefore, we have shown that the deep learning techniques, especially used through transfer learning and pretrained models like ResNet50 with a good dataset like HAM10000 can be a valuable tool in early skin cancer detection, even as an assistive technology, to enable faster and more accurate diagnoses by medical practitioners.

REFERENCES

[1] S. S. B. T. Sathvika, N. Anmisha, V. Thanmayi, M. Suchetha, D. E. Dhas, S. Sehastrajit, and S. N. Aakur, "Pipelined structure in the classification of skin lesions based on AlexNet, CNN and SVM model with bi-sectional texture features," IEEE Access, vol. 12, pp. 39842–39856, Apr. 2024.
[2] Mengistu, A. and Dagnachew Melesew Alemayehu. "Computer Vision for Skin Cancer Diagnosis and Recognition using RBF and SOM." (2015).
[3] K. Scott Mader, "Deep Learning Skin Lesion Classification," Kaggle, 2018. [Online]. Available: https://www.kaggle.com/code/kmader/deep-learning-skin-lesion-classification
[4] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA: MIT Press, 2016. ISBN: 978-0262035613.
[5] Mahbod, A. et al. "Transfer learning using a multi-scale and multi-network ensemble for skin lesion classification. Compute". Methods Program. Biomed. 193, 105475 (2020).
[6] He, K., Zhang, X., Ren, S., & Sun, J. (2016). "Deep Residual Learning for Image Recognition". Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778.
[7] Agarwal, P., & Hanmandlu, M. (2021). "Deep transfer learning for skin lesion classification with class imbalance handling". Biomedical Signal Processing and Control, 66, 102419.
[8] Datta, S. K., Shaikh, M. A., Srihari, S. N., & Gao, M. (2021). "Soft-attention improves skin cancer classification performance using VGG, ResNet, and InceptionResNetV2 models trained on the HAM10000 dataset". Proceedings of the International Conference on Machine Learning and Data Engineering (ICMLDE).
[9] Tschandl, P., Rosendahl, C., & Kittler, H. (2018).The HAM10000 dataset: "A large collection of dermatoscopic images for pigmented skin lesion classification". Scientific Data, 5, 180161
[10] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017)."Dermatologist-level classification of skin cancer with deep neural networks". Nature, 542(7639).
[11] Khan, M. A., Akram, T., Sharif, M., Javed, K., Raza, M., & Saba, T. (2020). "Skin lesion classification using deep learning and transfer learning architectures". Health Informatics Journal, 26(4), 2733–2749
[12] Revathy, B. D., Vijay, R., Ullas, B., S. N. H., & Dhyan M. (2023). "Skin Cancer Detection Using CNN (Convolution Neural Network) with AI Medical Assistant". International Journal For Multidisciplinary Research (IJFMR), 5(3), 45–51. E-ISSN: 2582-2160



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