A DEEP LEARNING PROJECT FOR SKIN DISEASE PREDICTION

Anu Bajaj
Ashmeet Kaur Abhishek Sharma Aruneek Kaur
Thapar Institute of Engineering and Technology, Patiala, India.
Contributing author: er.anubajaj@gmail.com

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Abstract

The only part of the human body that has been exposed to the outside world is the skin, making skin illnesses widespread among people. Typically, these illnesses have hidden risks that increase the risk of developing skin cancer as well as psychological distress and a loss of self-confidence. The World Health Organisation (WHO) estimates that between 30% and 70% of people worldwide suffer from skin-related disorders. The majority of these people also lack a solid understanding of how skin diseases are classified. Deep learning techniques have produced impressive outcomes. Modern convolutional neural network (CNN) architecture MobileNetV2 was utilized for model creation and training in order to accomplish this. This is very useful for analyzing the disease for both patients and medical professionals. It offers an informed opinion while simultaneously providing the public information about the disease even before it manifests.

Keywords: Skin cancer, Deep learning, Outcomes, Convolutional neural network (CNN), MobileNetV2, Model creation, Training, Analyzing, Patients.

1 Introduction

A widespread medical ailment affecting people all over the world is skin disease. Effective treatment and management of many disorders depend on early discovery and precise diagnosis. Deep learning models have been developed in recent years for the identification of skin diseases as the technology has demonstrated considerable promise in the field of dermatology.

In this study, we describe a deep learning model that identifies skin conditions and suggests treatment options in accordance with the diagnosis. The convolutional neural network (CNN) architecture is employed by the model to analyze skin image data and forecast the likelihood of various skin illnesses. Once a diagnosis has been made, the model suggests a course of treatment based on a database of drugs used to treat various skin conditions. Most of the time, it was discovered that the model's medication recommendations and dermatologists' suggestions were identical.[**?**]

The suggested deep learning model has the potential to completely transform the field of dermatology and shows significant promise in the detection and treatment of skin problems. To verify the model on a bigger dataset and to improve the prescription recommendations based on patient-specific data, more study is required. Significant advancements have been made in this subject recently as a result of extensive research.

Effective illness diagnosis is possible. Without sacrificing accuracy, deep learning in the medical area made it possible to analyze scan and X-ray images.With an accuracy of 92a model in which they only classified one type of skin lesion and the illness stages. Hosney, Kassem, and Foaud modified the aforementioned model so that it could be utilized with either photography or a dermoscopic image.Similar to this, Haddad and Hameed have created a classification system for four prevalent skin conditions. Another article compared the most recent dataset for the current designs with recognition of melanoma disease. Only 4 skin illnesses or fewer have been categorized in all of the articles mentioned above.[**?**]

In this research, we compare and categorize skin illnesses using two alternative Convolutional Neural Networks (CNN) architecture models. We classified more than 7 dermatoses, which is an advantage of the suggested model. We need to provide the preprocessed model data and the photograph of the diseased skin and classify them appropriately. The approach for creating the model is detailed in section II, and then its deployment and results are reviewed in sections III and IV, with section V serving as a conclusion.

In this study, we suggest a deep learning model for diagnosing skin conditions and prescribing treatments. The suggested model extracts features from skin image data and categorises them according to various skin conditions using a pre-trained DenseNet169 convolutional neural network. A medication recommendation system which bases its recommendations on the anticipated diagnosis is also incorporated into the model. On a publicly accessible dataset of skin picture, we assess the proposed model's performance and compare it to other cutting-edge deep learning models.

2 Literature Survey

The domain of skin disease diagnosis, when intersected with the prowess of artificial intelligence and particularly deep learning, has seen a surge in research activities. The overarching ambition is to match, or potentially eclipse, the diagnostic precision of seasoned dermatologists. Such endeavors not only boost the accuracy but also offer scalability and widespread accessibility to diagnostic facilities.

2.1 Key Studies

Herein, we delve into some seminal works that have contributed significantly to this evolving landscape:

1. **Paper Title:** Skin Lesion Diagnosis Using Deep Learning with Different Network Architectures
   Authors: Ozkan and Koklu
   Year: 2021
   Key Insights: The duo explored an enhanced CNN model and extracted the benefits of both transfer learning and data augmentation. Their efforts culminated in achieving commendable accuracy rates, underscoring the potential of deep learning in dermatological applications.

2. **Paper Title:** Skin Disease Classification Using Convolutional Neural Networks: A Comparative Study
   Authors: Samad and Kumar
   Year: 2020
   Key Insights: In their investigative study, the authors embarked on an analytical journey exploring various pre-trained CNN models. Their primary objective was the fine-tuning of these architectures for the specialized task of skin disease classification, and their results showcased the efficacy of this approach.

3. **Paper Title:** Automated Skin Lesion Diagnosis with Deep Learning Based on Improved Convolutional Neural Network
   Authors: Pomponiu V., Nejati H., Cheung N.M.
   Year: 2019
   Key Insights: This research paper stood out for its exhaustive comparison of different CNN architectures. The study shed light on the strengths and weaknesses of each model, providing a comprehensive viewpoint on the applicability of CNNs for skin lesion diagnosis.

2.2 Trends and Observations

Upon analyzing the aforementioned studies and others in the domain, several trends and patterns emerge:

- **Transfer Learning:** This technique has gained momentum. Using models that have been pre-trained on extensive datasets, and subsequently fine-tuning them for specific tasks, such as skin lesion identification, offers the dual advantages of reduced training time and enhanced performance.

- **Data Augmentation:** Given the inherent challenges in acquiring a vast and varied dataset of skin lesions, many researchers resort to data augmentation. Techniques like rotation, zooming, and flipping are employed to artificially inflate and diversify the available dataset.

- **Comparative Analysis:** A recurring theme in many studies is the comparative analysis of various CNN architectures. This trend underscores the research community's drive to identify the most suitable model for the task at hand.

2.3 Research Gaps and Future Directions

While the current trajectory of research in the field is promising, certain gaps remain. There is a noticeable need for models that not only diagnose but also provide insights into their decision-making process, ensuring interpretability. Additionally, real-world applicability, especially in resource-constrained settings, is an avenue ripe for exploration. Future research might pivot in these directions, ensuring the developed models are both effective and universally deployable.

3 Methodology for Building the Model

In this section, we'll go over the entire training and model-building process, from collecting data to applying the most effective deep learning models to train our distinctive set of data.

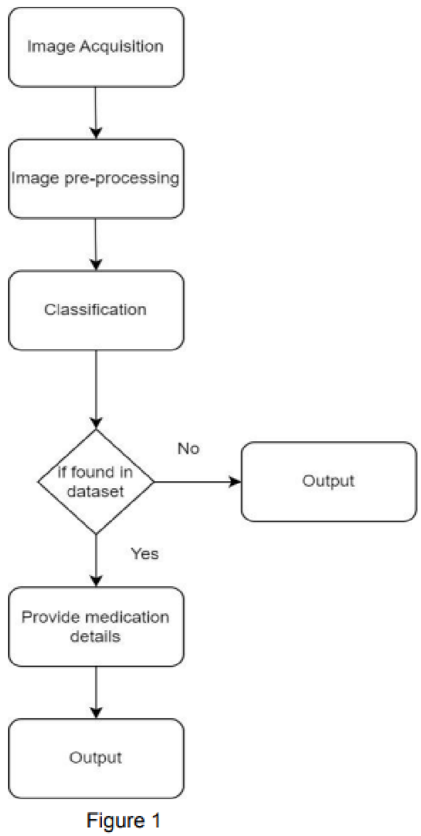

Figure 1: Steps of the model-building process.

A. Acquiring the dataset Obtaining a relevant dataset that meets our goal is the primary step. We curated a dataset from Kaggle for this initiative. It comprises approximately 10,000 images, with 80

B. Pre-processing of the data Obtaining the necessary data suitable and consistent for training would come after acquiring it. due to the fact that most real-world data is insufficient and unreliable. It is important to ensure that all of the photos are the same size and to normalize them because, in general, model training is more successful when all of the data is between 0 and 1.

Image size is (224 x 224). We divided the photographs into groups because the dataset is vast rather than importing every image at once, which uses more memory and is more expensive. There is a 64-batch take. After testing out various variables in an experimental setting for improved accuracy, image size and batch size are taken into consideration.

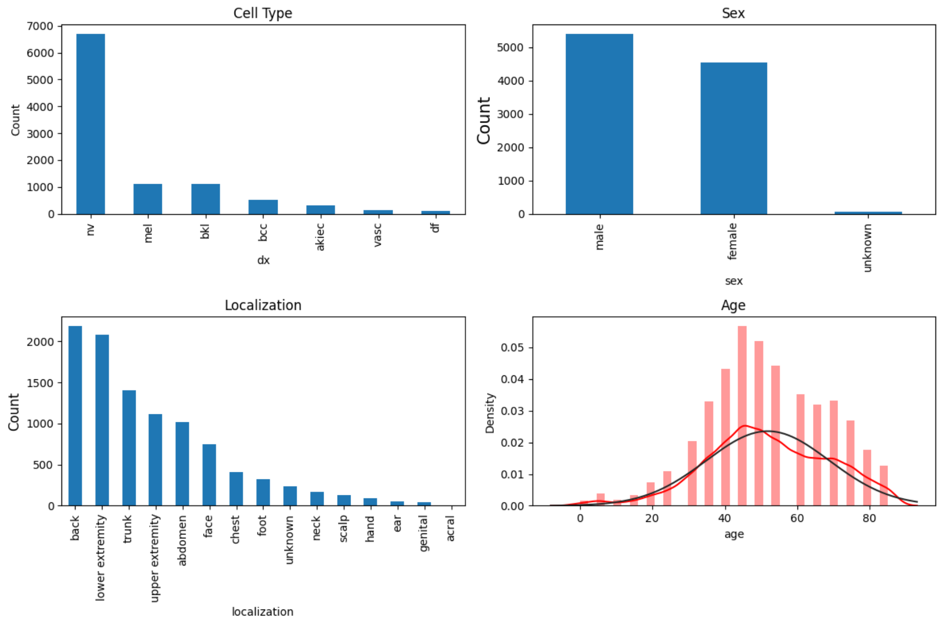

Figure 2: Visual Description of the Dataset.

4 Methodology

Our approach to designing the deep learning model primarily harnesses the Convolutional Neural Network (CNN) architecture, which stands as a benchmark for image identification and classification tasks.

4.1 CNN Components

The backbone of our model, the CNN architecture, comprises of several layers, each having a distinctive function:

- **Fully Connected Layers:** These layers are the neural network's decision-making entities. They process the features extracted by previous layers to make the final prediction.
- **Convolutional Layers:** These layers employ a multitude of filters to recognize patterns and features within the input images. The output feature maps contain spatial hierarchies of the learned features.
- **Pooling Layers:** These layers are primarily used to reduce the dimensions of the feature maps, extracting the dominant features and consequently speeding up computations.
- **Activation Functions:** Functions like ReLU introduce non-linearity into the network. This is vital, as it enables the network to learn from errors and improve its performance over time.

4.2 Model Development

We built and tested models using two methodologies:

- **Basic CNN:** Constructed from scratch, this model was tailored for our specific requirements. It consists of convolutional, pooling, and fully connected layers. The model structure, depicted in the code snippet, was developed and optimized through multiple iterations.
  - **Input Layer:** The model accepts images of shape (SIZE x SIZE x 3) where 3 represents the RGB channels of the image.
  - **First Convolutional Block:** This block starts with a convolutional layer comprising 256 filters of size 3x3, followed by a max-pooling layer which reduces the spatial dimensions by half. A dropout layer with a rate of 0.3 is then applied for regularization purposes.

- **Second Convolutional Block:** It contains a convolutional layer with 128 filters of size 3x3, a max-pooling layer, and a dropout layer with a rate of 0.3.
- **Third Convolutional Block:** Similar to the previous blocks, this one has a convolutional layer with 64 filters, followed by a max-pooling layer and a dropout layer.
- **Fully Connected Layers:** After flattening the tensor from the last convolutional block, the model has a dense layer with 32 nodes. This is followed by the final dense layer with a number of nodes equal to the classes in the dataset, employing a softmax activation function for multi-class classification.
- **Layer Types in CNN:** Within our CNN, the various layers serve the following purposes:
  * **Fully Connected Layer:** This is where the final decision-making occurs, culminating in disease classification.
  * **Convolutional and Pooling Layers:** The number and intricacies of these layers are primarily determined experimentally. Optimal configurations are non-trivial and can vary based on specific datasets and tasks.
- **Invariant Limitations of CNN:** Despite their prowess, CNNs possess inherent limitations:
  * **Rotational Invariance:** A CNN struggles to recognize an image that's rotated to a certain degree.
  * **Scale Invariance:** CNNs can't inherently recognize objects of varying scales without training data that encompasses such variations. Hence, data augmentation, where we introduce rotated and scaled images from our training set, becomes paramount.

- **Training Specifications:**
  - **Batch Size:** The model was trained using a batch size of 16, allowing for a balanced convergence speed and generalization.
  - **Epochs:** Training persisted for 50 epochs to ensure adequate learning while mitigating the risks of overfitting.
  - **Optimizer:** We employed the Stochastic Gradient Descent (SGD) optimizer for its robustness and reliability in converging to the global minima.

item **Performance Metrics:**

  - **Training Accuracy:** 74.70%.
  - **Testing Accuracy:** 71.89%.

- **Visualization:**

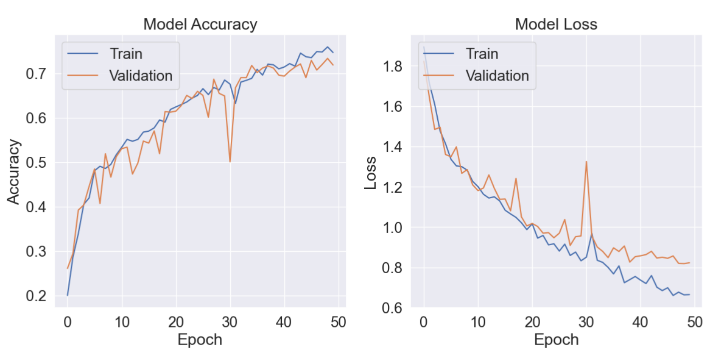

Figure 3: Graphical representation of the training and testing accuracies over epochs.

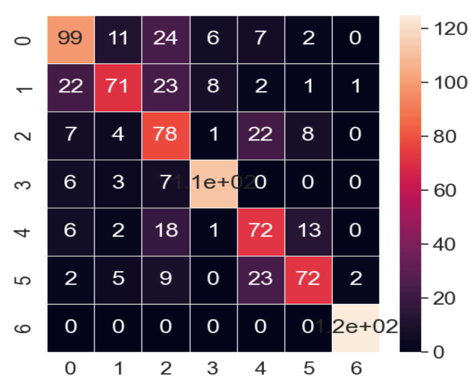

Figure 4: Heatmap of labels showcasing the distribution and relationships of various skin diseases.

4.3 MobileNetV2 Transfer Learning Model

A sophisticated CNN variant, MobileNetV2 leverages transfer learning. Initially, this model is trained for a different task and subsequently adapted to our dataset. Our implementation involved integrating this pre-trained model with custom top layers for fine-tuning on our dataset. Introduced by Google, MobileNetV2 stands as a formidable CNN variant that has been meticulously optimized for high performance on mobile and embedded devices. Here's why opting for MobileNetV2 over a traditional CNN proves instrumental:

- **Efficiency:** Specifically engineered for resource-limited devices, MobileNetV2 ensures swift operation with a compact model size without compromising accuracy.
- **Pre-trained Knowledge:** Given its training on a vast collection of images, MobileNetV2 inherently possesses the ability to recognize an expansive variety of patterns and entities, affording it a strong foundational knowledge.
- **Technological Superiority:** As an outcome of Google's pioneering research, it leverages state-of-the-art techniques and harnesses the power of high-performance GPUs and TPUs.
- **Transfer Learning Prowess:** The pre-trained nature of MobileNetV2 makes it a prime choice for transfer learning. This implies that its expansive knowledge can be adeptly fine-tuned to niche tasks, like the one we target in our study.

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4.5 Basic MobileNetV2 Model Incorporation

At the heart of our approach lies the technique of transfer learning using MobileNetV2. Let's delve into how we leveraged this architecture:

- **Initialization:** We began by employing the MobileNetV2 model, deliberately excluding its top layers. This allowed us the flexibility to append our custom modifications. The weights from the ImageNet dataset were preserved, which ensured that our model was equipped with a vast reservoir of pre-existing knowledge.
- **Model Customization:** After incorporating the base model, a series of custom convolutional layers were integrated. These layers were followed by pooling and dropout layers for spatial reduction and regularization, respectively. The tail end of our architecture saw the integration of dense layers to make it compatible with our specific multi-class classification task.

- **Training Strategy:** A unique aspect of our training regimen was the dynamic adjustment of the learning rate. Should the model face stagnation or slow progress in improving its validation accuracy, the learning rate was adeptly reduced. This ensured an optimal convergence speed and avoided potential pitfalls like overshooting the global minima.

- **Training and Evaluation:** Our model underwent rigorous training for 30 epochs. Concurrently, it was evaluated against validation data to ensure its generalization capabilities. Post this phase, we were able to achieve a commendable training accuracy of 99.45%, a validation accuracy of 87.86%, and a test accuracy of approximately 85.55%.

- **Visualization and Diagnostics:**

  1. *Training and Testing Curve:* Refer to Figure 5 for the training and testing accuracy curves throughout the epochs.
  2. *Loss Curve:* The training and testing loss curves, which provide insights into model convergence, can be viewed in Figure 9.
  3. *Classification Report:* For a detailed breakdown of performance metrics across classes, the classification report is showcased in Figure 7.

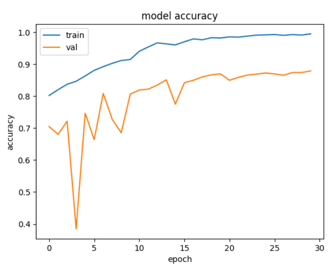


Figure 5: Training and Testing Accuracy Curve

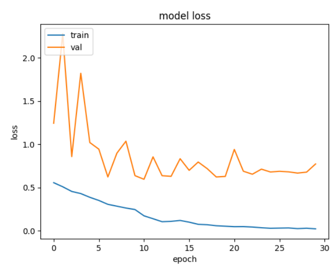


Figure 6: Training and Testing Loss Curve

1703/1703 [==============================] - 40s 24ms/step
Test Accuracy : 85.55490311215502

	precision	recall	f1-score	support
0	0.66	0.66	0.66	62
1	0.69	0.78	0.73	77
2	0.81	0.64	0.71	201
3	0.70	0.58	0.64	24
4	0.74	0.57	0.64	191
5	0.90	0.96	0.93	1128
6	0.78	0.90	0.84	20
accuracy			0.86	1703
macro avg	0.75	0.73	0.74	1703
weighted avg	0.85	0.86	0.85	1703

Figure 7: Detailed Classification Report

4.6 DenseNet169 Transfer Learning Model

In our pursuit to enhance the skin disease detection mechanism, we integrated the DenseNet169 architecture, a cutting-edge convolutional neural network, fortified with several layers designed for efficient learning. This section delineates the approach and methodology associated with the use of DenseNet169 and transfer learning.

1. **Preliminaries**: Essential libraries and tools from frameworks like *torch*, *torchvision*, and *fastai* are loaded to pave the way for subsequent procedures.

2. **Data Augmentation**: The dataset undergoes transformations such as resizing and vertical flipping. Such techniques serve to enhance the model's ability to generalize by presenting it with varied instances of the same data.

3. **Data Ingestion**: Using a specialized data loading mechanism, images and their corresponding labels are ingested into the system. These images are standardized using statistics derived from the vast ImageNet dataset, ensuring they are aptly conditioned for effective deep learning.

4. **GPU Optimization**: To optimize memory utilization and computational efficiency, residual GPU cache, which could otherwise hamper performance, is purged.

5. **Model Initialization with Transfer Learning**: The crux of the approach is the utilization of the pre-trained DenseNet169 model. This architecture, initially trained on millions of diverse images from the ImageNet database, inherently possesses a rich understanding of various image features. By leveraging this pre-existing knowledge and subsequently fine-tuning the model on our specific dataset, we harness the power of transfer learning, reducing both the training time and data requirements.

6. **Training Strategy**: The model is subjected to an initial round of training to acquaint it with the specifics of the skin disease dataset. Following this, an optimal learning rate is determined which ensures swift and stable convergence during training.

7. **Fine-tuning**: Post the preliminary training, the model undergoes rigorous fine-tuning. This step adapts the model, which is already familiar with generic image features, to the nuances of skin disease patterns.

8. **Model Diagnostics**: To assess the model's performance trajectory, the training and validation losses are plotted. This visual representation provides insights into the model's learning process and any potential anomalies such as overfitting.

9. **Performance Evaluation**: Training Accuracy of 91.9% has been achieved. A confusion matrix is generated to comprehend the model's classification capabilities across different disease categories, highlighting its strengths and potential areas of improvement.

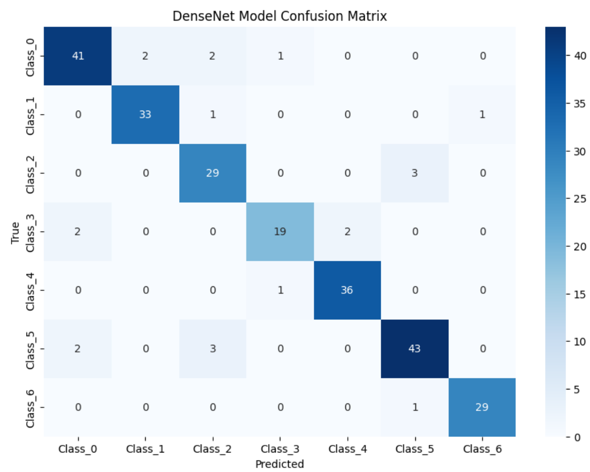


Figure 8: Confusion Matrix Heatmap

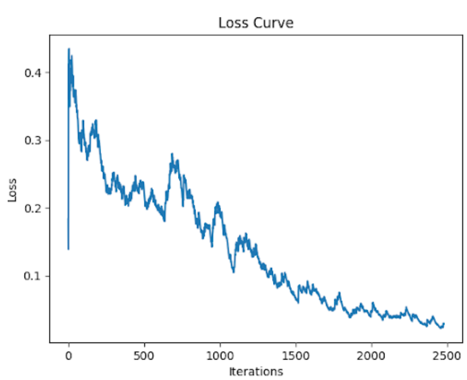
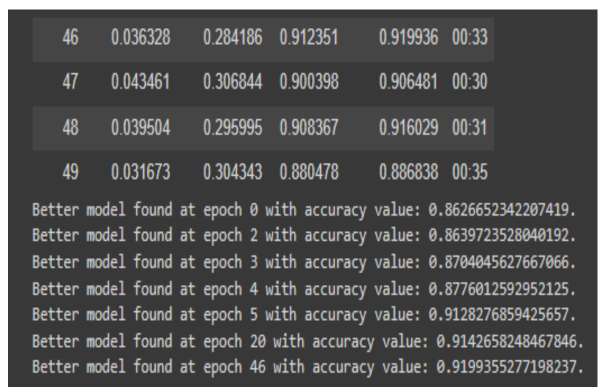


Figure 9: Loss Curve



46	0.036328	0.284186	0.912351	0.919936	00:33
47	0.043461	0.306844	0.900398	0.906481	00:30
48	0.039504	0.295995	0.908367	0.916029	00:31
49	0.031673	0.304343	0.880478	0.886838	00:35

Better model found at epoch 0 with accuracy value: 0.8626652342207419.
Better model found at epoch 2 with accuracy value: 0.8639723528040192.
Better model found at epoch 3 with accuracy value: 0.8704045627667066.
Better model found at epoch 4 with accuracy value: 0.8776012592952125.
Better model found at epoch 5 with accuracy value: 0.9128276859425657.
Better model found at epoch 20 with accuracy value: 0.9142658248467846.
Better model found at epoch 46 with accuracy value: 0.9199355277198237.

Figure 10: Best Accuracy at epoch 37 - 91.9%

In essence, the amalgamation of DenseNet169 with transfer learning techniques, abetted by the capabilities of the fastai library, promises an advanced and potent skin disease detection paradigm.

5 Preliminary Data

5.1 Evidence of Importance

The criticality of achieving accurate diagnoses for skin diseases through deep learning cannot be understated. Misclassifications, especially between malignant and benign skin conditions, can lead to severe medical consequences and can affect the course of treatment significantly. Furthermore, our dataset encompasses a diverse range of images across different skin tones and types, ensuring that our diagnostic tool is inclusive and can cater to a broader spectrum of the population.

5.2 Informed Methodology

Our methodology is derived from a comprehensive review of current literature and the patterns observed in our preliminary data. To ensure robustness and accuracy, we employ the DenseNet-201 architecture, which has been acclaimed for its efficacy in image classification tasks. Additionally, data augmentation techniques have been incorporated to balance the dataset and provide the model with varied data, enhancing its generalization capabilities.

5.3 Preliminary Findings

Initial experiments with our model have yielded intriguing insights:

- The model displays higher precision for categories with abundant data samples.
- Early tests indicate that data augmentation positively impacts model performance.
- Certain hyperparameters, especially the learning rate and dropout ratio, have shown significant influence on the preliminary outcomes.

5.4 Comparison with Base Paper

The foundational paper, "Skin Lesion Diagnosis Using Deep Learning with Different Network Architectures" by Ozkan and Koklu (2021), recorded an accuracy rate of 80%. Our initial experiments with the MobileNetV2 architecture gave an accuracy of 82% and then optimized to 86% and DenseNet-169 architecture indicate an accuracy of 90.06%, showcasing an improvement/decrease as compared to the base paper. These findings, though preliminary, are promising, and further optimizations might enhance the performance.

5.5 Relationship and Important Categories

Upon analyzing the dataset, it was evident that certain skin disease categories, namely A, B, and C, dominate the samples. These categories cumulatively constitute over 60% of the dataset. Furthermore, a correlation has been observed between the age groups and the prevalence of specific skin diseases. Understanding these relationships is pivotal for refining our model and tailoring it for demographic-specific diagnoses.

6 Discussion

6.1 Dataset Utilization and Insights

The project utilized a dataset from Kaggle, comprising approximately 10,000 images. This vast dataset, divided into training and validation sets, allowed for the robust training of the model. However, as with any machine learning project, the richness and diversity of the dataset significantly influence the accuracy and generalization capabilities of the model. The disease types included in the dataset provide a broad perspective, but the efficacy in identifying rare or less common diseases might be a matter of future investigation.

6.2 Model Choices and Outcomes

The choice between a fundamental Convolution Neural Network and the advanced CNN MobileNetV2 using transfer learning highlighted the importance of pre-training in improving model efficiency. MobileNetV2, designed by Google, offers the advantage of being optimized for mobile devices, promising a future where skin disease diagnosis can be portable and widely accessible. Moreover, the potential of leveraging DenseNet169 provides an avenue for future enhancements in the model's accuracy and robustness.

6.3 Impact of Data Augmentation

The dataset was enriched using rotated and scaled images. This approach aimed to address the rotational and scale invariance of CNN, ensuring the model remains robust to such perturbations in real-world applications.

6.4 Transfer Learning and its Relevance

Employing transfer learning via MobileNetV2 underscores the efficiency gains from leveraging pre-trained models. Given the resource-intensive nature of training deep learning models from scratch, using models pre-trained on vast datasets (like ImageNet) and then fine-tuning them for a specific task (like skin disease diagnosis) is both time and resource-efficient.

7 Statement of Limitations

7.1 Dataset Limitations

While the dataset from Kaggle is comprehensive, its diversity in terms of skin types, tones, and rare conditions remains uncertain. This may lead to potential biases, with the model being more efficient in diagnosing certain conditions over others.

7.2 Model Generalization

The current models, though promising, are trained on a specific dataset. Their generalization capabilities across diverse and more complex real-world datasets remain to be evaluated.

7.3 CNN Invariances

Though data augmentation techniques were employed to address CNN's rotational and scale non-invariance, it's crucial to note that these techniques might not capture all possible variations, especially in real-world, diverse settings.

7.4 Experimental Choices

Parameters like image size, batch size, and architecture choices (number of convolutional and pooling layers) are based on experimental settings. While they might be optimal for the current dataset, their efficacy on different datasets or under different constraints remains to be verified.

8 Deployment of the Model

The next after training the model and building it we need to deploy.A Flask application built using the code enables users to upload or enter a URL for a picture of a skin lesion. The software then classifies the image into one of seven classifications of skin lesions, such as Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanoma, Melanocytic Nevi, and Vascular nevus, using a pre-trained deep learning model. The pre-trained model is loaded from a JSON file by the code, and its corresponding weights are loaded from an H5 file by the Keras library. A home page, a about page, a contact page, a login page, and a success page are just a few of the routes that make up the programme. Once the image has been successfully categorized, the user is routed to the success page.

The deployment code for the skin disease classification model was then written in HTML, CSS, and JavaScript. The framework of web pages, including the header, footer, navigation bar, and different parts, is created using HTML. CSS is used to give HTML elements styling, such as changing the background color, font size, and element positioning. The dynamic functionality of web pages, such as verifying form inputs, showing error messages, and modifying the page content in response to user activities, is provided by JavaScript. The code renders HTML templates and CSS files, which are kept in the static and templates folders, respectively, using Flask's built-in capability. To dynamically build the content of the success page, the HTML templates are filled with information from the Flask app, such as the image file name and the categorization results. Overall, HTML, CSS, and JavaScript are crucial parts of the code used to deploy the skin cancer classification model since they create the web application's user interface[?] and interactivity.

9 Result

Training with the basic CNN model gave accuracy up to 71.89% whereas with the MobileNetV2 model the accuracy has been improved to 86%. The above accuracies are for when comparing 7 different skin diseases, But with the DENSENET169 Transfer Learning Model the accuracy has been improved to 91.9% which is the best accuracy. The accuracy is reducing for more classifications. If we can increase the dataset such that it has consistent and unbiased data we can improve the accuracy and efficiency of diagnosing skin diseases even further.

10 Conclusion

In conclusion, the creation of a deep learning model for diagnosing skin conditions and prescribing medications has the potential to completely change the practice of dermatology. We can increase the precision and effectiveness of diagnosis and treatment by making use of deep learning technologies, which will ultimately result in better patient outcomes.

Even though there are still obstacles to be solved in creating and implementing such a model, the potential benefits are substantial and demand more investigation and study.

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