CIS-583-001

DEEP LEARNING

SKIN CANCER CLASSIFICATION

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Abstract:

In this final project, we addressed the problem of classifying different skin lesions based on HAM10000 dataset which has a collection of dermatoscopic images from different populations, acquired and stored by different modalities. Also, the severity of these skin lesions is categorized into two parts: Benign, which is less dangerous and Malignant considered to be life threatening. Based on metadata.csv(contains essential information of each image) from the dataset Exploratory Data Analysis has been performed to Categorize skin lesions into Benign and Malignant. In addition to this , insights like which age groups are most affected, Age distribution through different diagnosis, counts for each type of lesion, Location of the lesion on body parts etc... are obtained through Data Visualization.

Our main goal is to develop a deep learning model by using CNN(Convolutional Neural Network) which is best used to classify medical images and to support clinical decision making. The chosen topic revolves around supervised learning as each image in the dataset has a specific diagnosis label which helps the model to identify complex patterns.

The primary objective is to build a fully functioning skin cancer classification prototype using Convolutional Neural Networks (CNNs), and to improve upon the midterm work through fine-tuning, class balancing, and the use of advanced pretrained models.

Problem Statement/Objectives:

Skin cancer is among the most common cancers globally, with millions of cases diagnosed each year. Early diagnosis is crucial for the people who are being affected by these diseases. Dermatology Experts are limited in many regions, and it is sometimes difficult to make accurate classification among various diseases. Our motivation stems from the rising incidence of skin cancer globally and the shortage of expert dermatologists in many regions. We aim to demonstrate that deep learning, especially CNNs, can assist in early and accurate classification of skin lesions. We strive to improve accuracy through data handling techniques and advanced model architecture.

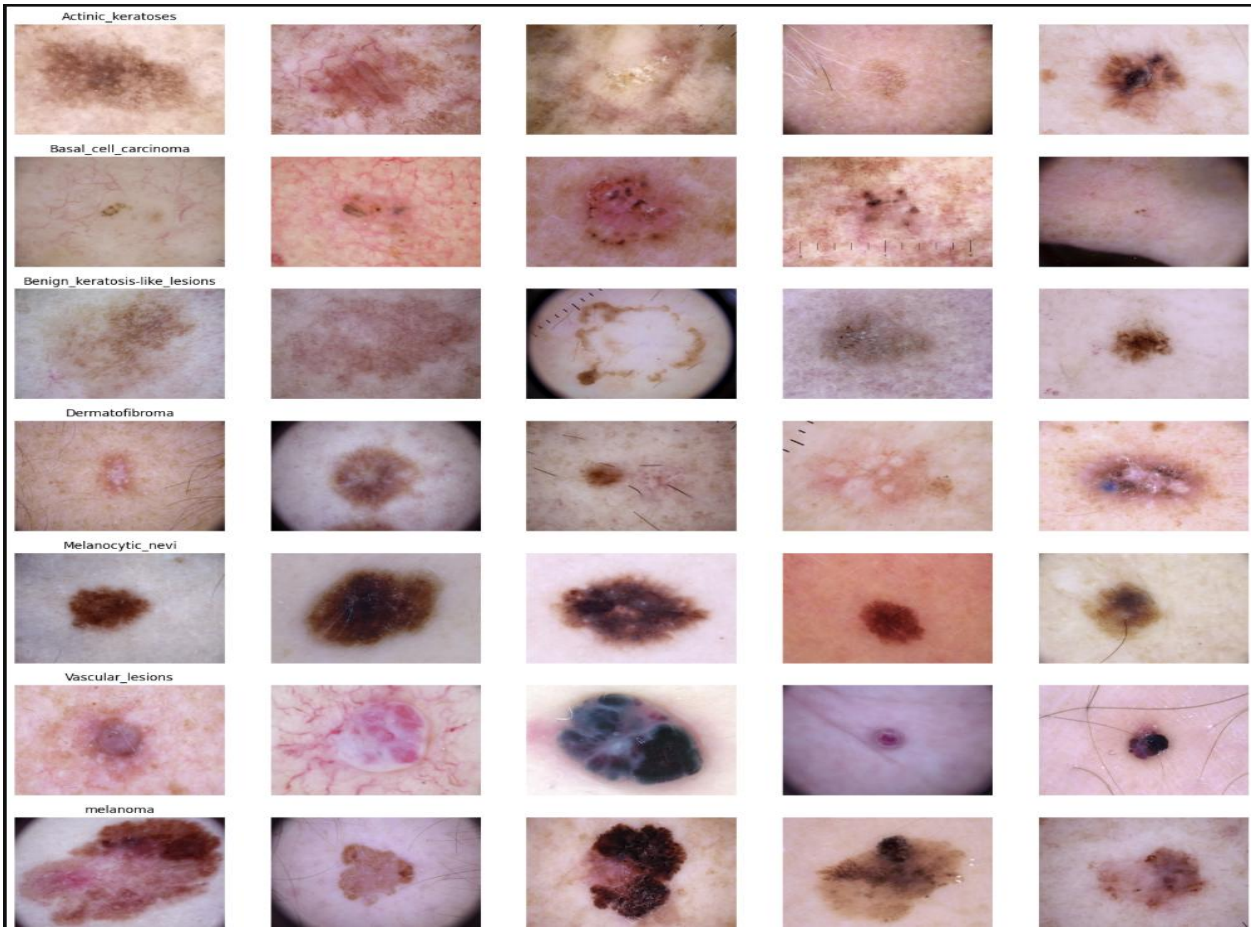
Background and AI type:

Deep learning is a powerful subset of machine learning, using artificial neural networks to mimic the human brain's ability to learn. This project utilizes Supervised Learning, where models are trained on labeled data. CNNs are ideal for image classification due to their ability to automatically and adaptively learn spatial hierarchies.

Dataset Description:

The dataset used in this project is the HAM10000 ("Human Against Machine with 10,015images") dataset, which is a widely recognized benchmark dataset for skin lesion analysis and classification tasks. The size of each image is 600*450 pixels in PNG format and dataset size is 2GB approximately.

Each image in the dataset is labelled with one of the 7 classes of lesion. Classes include a representative collection of all important diagnostic categories in the realm of pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc). The diversity in image sources ensures a wide variation in lesion types, skin tones, and image quality.



Metadata.CSV:

This file contains all the necessary information of every image included in the dataset. This includes various columns such as lesion_id,image_id,dx(diagnosis),dx_type, age, sex and localization.

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

Based on the data frame we linked each image id to a file path(will be converted into tensors) used for model training. Also, we created labels for the diagnosis from 0 to 6 named lesion_ID as the model requires numerical class label for supervised learning. Created a column named lesion_type to provide readability of various lesion types.

```
imageid_path_dict = {os.path.splitext(os.path.basename(x))[0]: x
                     for x in glob(os.path.join(base_skin_dir, '*', '*.jpg'))}

lesion_type_dict = {
    'nv': 'Melanocytic_nevi',
    'mel': 'melanoma',
    'bkl': 'Benign_keratosis-like_lesions',
    'bcc': 'Basal_cell_carcinoma',
    'akiec': 'Actinic_keratoses',
    'vasc': 'Vascular_lesions',
    'df': 'Dermatofibroma'
}

lesion_danger = {
    'nv': 0,
    'mel': 1,
    'bkl': 0,
    'bcc': 1,
    'akiec': 1,
    'vasc': 0,
    'df': 0
}
```

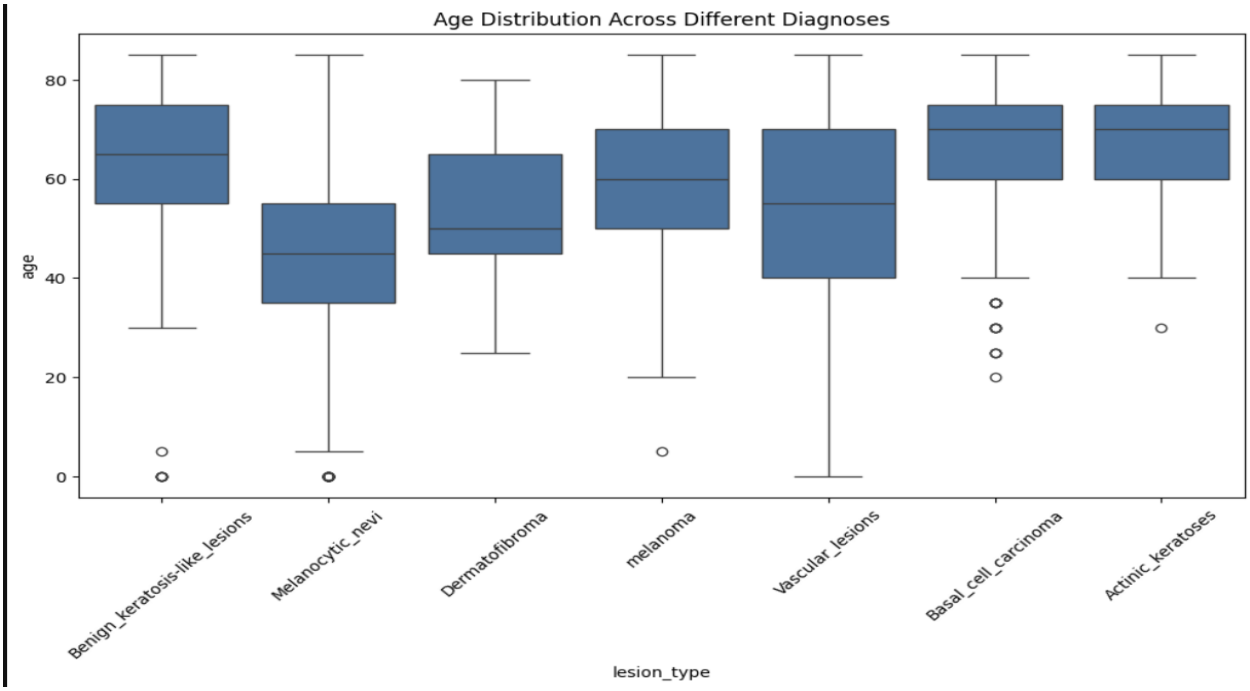
```
df1=skin_df.copy()

df1['lesion_type'] = df1['dx'].map(lesion_type_dict)
df1["path"] = skin_df["image_id"].map(imageid_path_dict.get)
df1['malignant'] = df1['dx'].map(lesion_danger)
df1['lesion_ID'] = pd.Categorical(df1['lesion_type']).codes


df1.head()
```

	lesion_id	image_id	dx	dx_type	age	sex	localization	lesion_type	path	malignant	lesion_ID
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp	Benign_keratosis-like_lesions	C:\Users\sivan\anaconda3\envs\DL\data\dlprojda...	0	2
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp	Benign_keratosis-like_lesions	C:\Users\sivan\anaconda3\envs\DL\data\dlprojda...	0	2
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp	Benign_keratosis-like_lesions	C:\Users\sivan\anaconda3\envs\DL\data\dlprojda...	0	2
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp	Benign_keratosis-like_lesions	C:\Users\sivan\anaconda3\envs\DL\data\dlprojda...	0	2
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear	Benign_keratosis-like_lesions	C:\Users\sivan\anaconda3\envs\DL\data\dlprojda...	0	2

Insights Obtained from metadata.csv:



Data Acquisition Challenges:

- **Imbalanced Dataset**:
  The majority class (melanocytic nevi) is overrepresented, leading to biased model performance. Techniques like class weighting and data augmentation were necessary to mitigate this.

```
lesion_type
Melanocytic_nevi                  6705
melanoma                          1113
Benign_keratosis-like_lesions     1099
Basal_cell_carcinoma               514
Actinic_keratoses                  327
Vascular_lesions                   142
Dermatofibroma                     115
Name: count, dtype: int64
```

- **Image Resizing**:
  High-resolution images were resized to 100x75 for the basic CNN and 192x256 for pretrained models to ensure manageable computation without significant loss in image quality.

- **Data Noise**:
  Artifacts such as hair and varying lighting conditions affected image clarity. Minimal preprocessing (e.g., normalization) was used to retain essential lesion features while reducing noise impact.

Model Overview:

For this project, we defined three CNN models for classification of different skin lesions, each model was chosen to progressively enhance complexity, feature extraction capability and accuracy. The models we used are:

1. Basic CNN Architecture
2. InceptionResNetV2
3. EfficientNetB4
4. DenseNet121

Basic CNN Architecture:

A Convolutional Neural Network CNN is a type of deep learning model particularly effective for image classification. It uses convolutional layers to automatically detect

important features like edges, textures and shapes. Here we have developed a basic CNN model from scratch.

- Input Shape: (75, 100, 3) for RGB images
- Layers: Two convolutional layers followed by max-pooling layers. MaxPooling reduces spatial dimensions and helps focus on dominant features.
- Dense Layers: Fully connected layers for final classification after flattening the feature map.
- Activation Functions: ReLU for hidden layers and Softmax for the output layer to yield class probabilities.
- Dropout Regularization: Used to prevent overfitting by randomly deactivating neurons during training.
- Optimizer: Adam optimizer adjusts weights efficiently using gradients.
- Loss Function: Categorical Crossentropy is used to handle multiclass classification.

InceptionResNetV2:

InceptionResNetV2 merges the benefits of Inception architectures with residual connections from ResNet. This hybrid structure allows the model to go deeper without suffering from vanishing gradients, making it highly suitable for extracting intricate features from medical images.

We have resized input images to 224x224, matching the standard input size for this architecture. Transfer learning was applied by freezing the bottom layers and training the top layers. After initial convergence, the model was fine-tuned with a smaller learning rate for better performance.

EfficientNetB4:

EfficientNetB4 is part of the EfficientNet family of models known for their efficient scaling of depth, width, and input resolution. This architecture was selected for its ability to achieve high accuracy with fewer parameters and lower computational overhead.

We have resized input images to 380x380, the required resolution for B4. The model was imported with pretrained ImageNet weights, and custom classification layers were appended. Fine-tuning was applied after initial training of the top layers.

DenseNet121:

DenseNet121 was chosen for its unique connectivity pattern where each layer receives input from all preceding layers. This results in efficient feature reuse and improved gradient flow, particularly beneficial for deep networks.

We have used an input size of 224x224, compatible with the pretrained DenseNet121. A custom classification head was added, and similar training and fine-tuning steps were followed.

Methods:

- Tools and Libraries: Python, TensorFlow, Keras, Pandas, NumPy, Matplotlib, Seaborn
- Environment: Google Colab and Jupyter Notebook
- Preprocessing Techniques:
    - Resizing
    - Normalization
    - One-hot encoding of categorical labels
    - Data Augmentation using rotation, zoom, flips
- Training Strategy:
    - Train validation test split: 70-20-10
    - Use of weighted loss to handle class imbalance
    - Batch size: 32
    - Epoch tuning with early stopping

Results:

The results of our project are based on through evaluation across training, validation and test sets using multiple deep learning architectures. Each model was assessed based on accuracy, precision, recall, F1-score and confusion matrix results.

Basic CNN:

- Accuracy: Achieved approx. 75% accuracy on the test set.
- Strengths: Performed well for the majority class (melanocytic nevi)
- Weakness: This struggled with minority classes such as dermatofibroma and actinic keratosis due to the inherent class imbalance.
- The confusion matrix shows a strong bias toward predicting the most frequent class.
- While this model proved as useful as a baseline, this model lacked the depth to capture features necessary for distinguishing between similar skin lesion types.

InceptionResNetV2:

- Accuracy Achieved up to 78% validation and test sets.
- Leveraged residual connections to go deeper without overfitting, resulting in improved F1-scores for difficult classes like actinic keratosis (akiec).
- Training required more resources and time due to the deeper architecture.
- Insights: The hybrid structure allowed better handling of nuanced patterns in skin lesions. However, performance gains over InceptionV3 were incremental rather than revolutionary.
- Confusion Matrix: Showed better class separation overall, with reduced confusion in previously overlapping lesion pairs.

EfficientNetB4:

- Accuracy: This model achieved the highest performance across all sets up to 81% on test set.
- F1-Scores: Most balanced across all lesion classes, with significant improvements in predicting melanoma and vascular lesions.

- Demonstrated the best generalization capability. Efficiently handled high intra-class variability and low inter-class separability.
- Fine-tuning and augmentation strategies played a vital role in stabilizing learning.
- Confusion Matrix: We can see clear reduction in false negatives for critical conditions like melanoma and Improved recall and precision led to more dependable diagnostic predictions.

DenseNet121:

- Accuracy: Achieved around 78–79% on the validation set.
- Dense connections encouraged feature reuse and stabilized gradients, resulting in robust training and good generalization.
- The model was memory-intensive and showed early signs of overfitting in longer training sessions.
- DenseNet handled subtle features well, especially in benign vs malignant lesion separation, though performance was slightly below EfficientNetB4.
- Confusion Matrix: Provided competitive separation across most classes, with strong precision in common categories and decent recognition of rare ones.

The progression from a simple CNN to EfficientNetB4 resulted in a noticeable performance boost.

EfficientNetB4's architecture enabled better discrimination between related classes and outperformed other models in all key metrics.

The combined use of transfer learning, data augmentation and class weighting significantly enhanced the overall robustness and accuracy of the system.

Conclusion:

Project Impact:

This project validates the application of CNN-based deep learning models for aiding dermatologists in skin cancer classification. By using models like EfficientNet, we can see the potential in building scalable and reliable diagnostic tools that reduce human error and increase early detection capabilities.

Summary:

From a basic CNN to advanced transfer learning architectures, this project showed an iterative improvement through rigorous model development and evaluation. Addressing class imbalance and leveraging pretrained networks significantly boosted performance. Comparative analysis confirmed that sophisticated models like EfficientNetB4 are more effective in medical imaging tasks where precision and sensitivity are crucial.

Reflection on the Project:

We have learned a lot about real deep learning by working on this project that combined image analysis with healthcare. Dealing with problems like overfitting and limited computer power taught us a lot. It was great to use real data and see how small changes could have big effects.

Future Work:

For future improvements, the model can be extended by integrating clinical metadata (e.g., patient age, lesion location) to enrich feature input. Additionally, deploying the trained model in a real-time web or mobile application could translate this research into a functional diagnostic aid. Further experiments using other state-of-the-art models like Vision Transformers or ensemble approaches could be explored to improve classification accuracy and robustness.

Project Overview:

In this project we have implemented multiple CNN-based approaches to classify skin lesions using the HAM10000 dataset. From designing basic CNN to fine-tuning advanced architectures, we have explored preprocessing, data balancing, and rigorous evaluation. The final model, EfficientNetB3, proved highly effective and ready for real-world testing.

Team Experience:

Working together helped us split up the work and get better results. We each handled different parts like preparing data, building the model, checking it, and writing about it. This made the project go well. Teamwork really helped us solve problems faster and get more done. It also felt like a real job, which was good practice for the future.

References:

Philipp Tschandi, Cliff Rosendahl and Harald Kittler “The HAM10000 dataset, a large collection of multi-sources meatoscopic images of common pigmented skin lesions” https://www.nature.com/articles/sdata2018161

Duyen N. T. Le, Hieu X. Le, Lua T. Ngo, Hoan T. Ngo “Transfer learning with class-weighted and focal loss function for automatic skin cancer classification” https://arxiv.org/abs/2009.05977

Abdulmateen Adebiyi, Nader Abdalnabi, Emily Hoffman Smith, Jesse Hirner, Eduardo J. Simoes, Mirna Becevic, Praveen Rao “ACCURATE Skin Lesion Classification using multimodal learning on the HAM10000 dataset” https://www.medrxiv.org/content/10.1101/2024.05.30.24308213v1

Skin Cancer MNIST: HAM10000