Project Title: Ensemble Learning and Transfer Learning for Skin Cancer Detection: A Study on HAM10000 Dataset

Team members:

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Problem statement:

Skin cancer is a leading cause of death worldwide, and early detection is crucial for effective treatment. In this study, we aim to develop a robust and accurate skin cancer detection system using deep learning techniques on the HAM10000 dataset. We propose to investigate the effectiveness of transfer learning, ensemble learning, and convolutional neural networks (CNNs) for skin lesion classification. Specifically, we aim to fine-tune pre-trained CNNs, such as VGG or ResNet, on the HAM10000 dataset using transfer learning techniques. Additionally, we propose to investigate the effectiveness of combining multiple CNNs using ensemble learning methods.

Related work:
We have read through a few papers in which state of art methods have used CNNs and a few latest papers also used EfficientNet (designed by Google).
Below listed are some of the skin cancer detection works using machine learning and deep learning approaches we have gone through:

[1] 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), 115-118. doi: 10.1038/nature21056.
[2] Goyal, A., & Navchetan Awasthi, A. (2020). An ensemble of deep learning techniques for skin cancer detection. Journal of Medical Systems, 44(9), 175. doi: 10.1007/s10916-020-01589-2.
[3] Noel Codella, Veronica Rotemberg, Philipp Tschandl, M. Emre Celebi, Stephen Dusza, David Gutman, Brian Helba, Aadi Kalloo, Konstantinos Liopyris, Michael Marchetti, Harald Kittler, Allan Halpern: "Skin Lesion Analysis Toward Melanoma Detection 2018: A Challenge Hosted by the International Skin Imaging Collaboration (ISIC)", 2018; https://arxiv.org/abs/1902.03368
[4] Tschandl, P., Rosendahl, C. & Kittler, H. The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Sci. Data 5, 180161 doi:10.1038/sdata.2018.161 (2018).

Initial hypothesis:

The main research question we want to investigate is whether an ensemble transfer learning approach with CNNs can improve the accuracy and generalization of skin cancer detection on the HAM10000 dataset. We expect our results to show that our proposed method outperforms existing methods and achieves a high accuracy in classifying skin lesions into different types of skin cancer.

Dataset(s):

Dataset source (link and reference)	https://challenge.isic-archive.com/data/#2018
Number of instances	10015
Number of features	Each image is an RGB image of dimensions 600x450. So the number of features will be 810000 per image.
Class distribution (# instances in each class, if applicable)	1. Nevus (melanocytic or non-melanocytic): 6705 2. Melanoma: 1,113 images 3. Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis): 1099 4. Basal cell carcinoma: 514 5. Actinic keratosis / Bowen's disease (intraepithelial carcinoma): 327 6. Vascular lesion: 142 7. Dermatofibroma: 115
Dataset splits	70% Training, 15% validation and 15% Testing
Preprocessing steps	Loading the image data, Resizing the images, Normalizing the Pixel values and augmentation along with splitting the dataset.

Method(s):

Transfer learning will allow us to leverage pre-trained CNN models, such as VGG or ResNet, and fine-tune them on the HAM10000 dataset to improve the performance of the skin lesion classification task. Ensemble learning will enable us to combine multiple CNNs to improve the accuracy and robustness of the skin cancer detection system.

Current state of art methods have used CNNs and a few latest papers also used EfficientNet (designed by Google) which achieved improved accuracies. Novelty about our approach compared to previous work is the use of ensemble learning with transfer learning. While previous studies have demonstrated the effectiveness of transfer learning and ensemble learning separately, combining them has not been widely explored in the context of skin cancer detection on the HAM10000 dataset. We plan to use the Python programming language and popular deep learning libraries such as Keras, TensorFlow, and Scikit-learn to implement my proposed method.

Evaluation:

To quantitatively measure the performance of the solution, we plan to use several evaluation metrics commonly used in image classification tasks, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). We will split the HAM10000 dataset into training and validation sets to train the model and will use the test set to evaluate the performance of the proposed skin cancer detection system. In addition to the quantitative evaluation, we also plan to conduct a qualitative assessment of the proposed skin cancer detection system. We will visualize the CNN models' attention maps to understand which regions of the skin lesion the models focus on to make a prediction. A comprehensive literature review of the state-of-the-art methods for skin cancer detection on the HAM10000 dataset will also be performed. We can also compare the computational complexity and resource requirements of the proposed method to other existing methods to assess its practicality. We can also visualize the attention maps and conduct a qualitative assessment of the proposed system's interpretability.

Management plan:

To manage the project implementation, we plan to divide the work into multiple components: code management, data preprocessing, model development, model evaluation, and report writing. During initial phases each of us will work on the research of algorithms, dataset collection and data preprocessing, then each group member will be responsible for a specific component, but we will collaborate closely throughout the project to ensure consistency and continuity. We plan to use project management tools such as GitHub to manage the project and to have a vision of contributions by each person. Holding accountability requires a shared commitment to the group’s goals. By establishing clear expectations, regular check-ins, and positive reinforcement, group members can work together effectively and ensure accountability. We have created a whatsapp group for our communication and we will also schedule regular zoom meetings and communicate via online chat and video conferencing to discuss progress, challenges, and feedback.