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Enhancing Skin Disease Classification: A Novel Approach With Tailored Loss Functions And SMOTE

Sumeet Ghumare[1], Pranav Chothave[2], Yadnyasen Shinde[3], Tushar Mamadge[4], Komal Gaikwad[5]

[1]*Department of Artificial Intelligence and Data Science, VPKBIET, Baramati*
[2]*Department of Artificial Intelligence and Data Science, VPKBIET, Baramati*
[3]*Department of Artificial Intelligence and Data Science, VPKBIET, Baramati*
[4]*Department of Artificial Intelligence and Data Science, VPKBIET, Baramati*
[5]*Department of Artificial Intelligence and Data Science, VPKBIET, Baramati*

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Abstract - Although skin disease like skin cancer is a common health problem worldwide, early identification is crucial to its recovery. By using medical photos, the rise of artificial intelligence (AI) has transformed the detection of skin diseases. Despite the reality that various deep learning models have been created with this goal in mind, class imbalance in multi class classification all poses a serious difficulty and imbalance among the classes. This work offers a novel strategy to reduce class imbalance in the categorization of skin diseases, leading to significant accuracy gains. One of the largest skin cancer datasets currently accessible, it consists of 33,106 dermoscopy photos from seven different kinds of skin diseases as a starting point. The main goal is to enhance skin disease classification algorithms' performance on this imbalance dataset. We are going to use a two-pronged strategy to combat the class disparity and GAN (Generative adversarial network) Based Oversampling or Meta-learning in order to successfully equalize the representation of each class during training, we first design a balanced Dynamic Mini-Batch Size logic, SMOTE (Synthetic Minority Oversampling Technique) and Augmenter. Second, we provide a new loss function designed to take into account the unique features of the dataset. The outcomes are startling. These findings underscore the efficacy of our hybrid approach in training deep convolutional neural networks for imbalanced skin disease datasets. By combining data-level balancing techniques with a carefully designed loss function at the algorithm level, we address the challenge of among the classes, paving the way for more accurate and reliable skin cancer diagnoses.

***Key Words*:** Dermoscopy images, DenseNet169, Convolution neural network, SMOTE (Synthetic Minority Over-sampling Technique, GAN(Generative adversarial network), Mini-Batch Logic, Augmenter

1. INTRODUCTION

An worrying number of five million new cases of skin cancer are identified in America alone each year, making it an increasing health concern worldwide. Skin cancer is associated with a variety of skin lesions, the deadliest of which is melanoma because of its high fatality rate. The good news is that 95 if they are discovered early.

Dermatologists often do a pathological study and visual assessment of skin lesions when they suspect malignancy. Dermoscopy has demonstrated considerable potential in this regard as an imaging method that improves the viewing of deeper skin lesions. We may even have smartphone-compatible, reasonably priced dermoscopy equipment soon.Artificial intelligence has been used in a number of research to develop predictive algorithms using imagery of skin lesions. Initially, to classify skin lesions, researchers used aspects that were manually created. On the other hand, deep convolutional neural networks (CNNs), which have shown exceptional performance in image recognition tasks, are the focus of the more recent development.

But there are difficulties. There is often an imbalance in the classification performance across illness classes due to the restricted and uneven nature of the datasets employed. For example, a great deal of research has been done on binary melanoma classification, with very little study done on multi-class classification. Recent efforts, such as the 2018 and 2019 ISIC challenges, offered larger datasets and saw several research teams competing to address these concerns. Even the best models from these competitions, nevertheless, show a notable disparity in class performance, particularly between nevus and melanoma.

In this study, we offer a hybrid system for dataset balancing, which combines data-level balanced mini-batch logic with real-time image augmentation. We predict improving the multi-class skin-disease classification's performance in the meantime by constructing a new algorithm-level loss function. Our study is centered on two new contributions: a data-level technique that, during training, evenly shares photos among classes in a batch. To address the class imbalance, we suggest using real-time picture augmentation in con- junction with a balanced mini-batch logic. A mixed approach that combines data-level and algorithm-level techniques such as SMOTE and Augmenter to address class imbalance. We include two hidden layers into a fully connected layer to improve neural network learning.

Additionally, methods like dropout and batch normalization are used to improve the solution's performance. All in all, our goal is to present an all-encompassing strategy to overcome the existing drawbacks in multi-class skin-disease labeling.

2. Skin Disease Classification

A. Convolutional Neural Network

Convolutional Neural Networks (CNNs) have demonstrated significant success in the field of skin disease classification, leveraging their ability to automatically learn hierarchical features from image data.The process initiates with the curation of a labeled dataset, comprising synthetically generated images,laying the groundwork for CNN training.

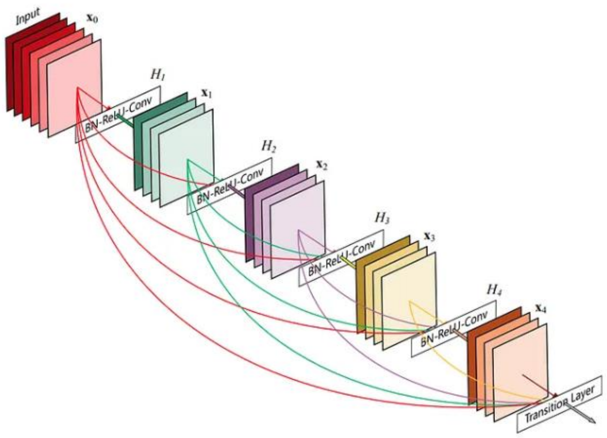

Fig -1: CNN Architecture

B. DenseNet169 Model

DenseNet169 is a popular convolutional neural network (CNN) architecture used for feature extraction in image classification tasks. It was introduced in a research paper titled "Densely connected convolutional networks" by G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger in 2017. DenseNet169 is known for its dense connectivity pattern, where each layer is connected to every other layer in a feedforward manner.

C. Mini Batch Logic

Deep convolutional neural networks (CNNs) require a large number of dataset samples in order to be trained. However, because of the dataset's complexity and resource-intensive nature, it is not feasible to perform optimal calculations on it at each training iteration. In order to overcome this, batch logic is used to split the dataset into smaller subsets, and for each iteration, a subset is used rather than the full dataset. Every iteration introduces a dynamic distribution of both majority and minority classes, which differs from their distribution in the original dataset due to the random selection of photos within these subsets.

D. Real – time Augmentation

Real-time augmentation and the suggested custom minibatch logic are used to prepare training data before the CNN extracts features from it. Real-time augmentation creates images as they are chosen, in contrast to offline augmentation, which augments the complete dataset before selecting a subset at random for the training batch. By doing this, it is ensured that a batch of photos does not originate from the same initial image, as offline augmentation may do. This enhances the neural network training process, particularly when paired with the CLF loss function.

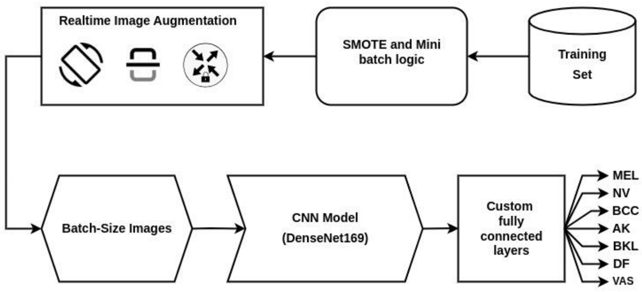

Fig -1: System Architecture

E. Synthetic Minority Over-Sampling Technique (SMOTE)

The Synthetic Minority Over-Sampling Technique, commonly known as SMOTE, is a statistical method designed to rectify class imbalances in datasets by generating synthetic instances of the minority class. This technique proves particularly valuable in scenarios where data distribution is skewed, a situation that can introduce bias into machine learning models, favouring the majority class. SMOTE operational mechanism involves selecting random instances from the minority class and identifying the k-nearest neighbours for each of these instances, with a typical setting of k being 5. Subsequently, synthetic samples are generated through a process of interpolation between the chosen instance and its neighbours. This iterative process continues until a balanced representation between the minority and majority classes is achieved. A distinct advantage of SMOTE lies in its avoidance of mere duplication of examples from the minority class, a practice that could lead to overfitting. Instead, SMOTE synthesizes new examples, enriching the dataset with additional information. This characteristic makes SMOTE a potent tool for enhancing the performance of ML models, particularly in the context of imbalanced datasets. Implementation of SMOTE is facilitated by various programming libraries, such as scikit-learn in Python, offering customizable parameters like sampling strategy and random state. This adaptability renders SMOTE a widely adopted technique for addressing class imbalance in diverse machine learning tasks.

F. Augmentor

In the realm of machine learning, an ”augmenter model” is not a standalone entity but a collective term for strategies that expand and diversify a dataset. These methods are akin to a set of creative brushes that an artist uses to enhance and vary their canvas, ensuring that the artwork—a predictive model—can interpret the real world with greater accuracy and flexibility. For images, imagine taking multiple snapshots with slight variations—flips, rotations, or lighting changes—to provide a camera with a broader view of the world it's trying to capture. In text, it's like an author rephrasing sentences or deploying synonyms to enrich the narrative and prevent their story from being too predictable. With audio, augmentation introduces different background sounds, mimicking the way we hear voices in diverse settings, encouraging a model to focus on the spoken words rather than the environment. Synthetic data generation is akin to a playwright crafting additional characters and dialogues to add depth to the original script. By augmenting datasets, just as rehearsals prepare actors for varied stage scenarios, models are trained to avoid overfitting—the equivalent of an actor reciting lines perfectly in rehearsal but faltering in an unforeseen live performance. This rich training equips models to better understand and predict new, unseen data, just as a well-rounded education prepares students for a multitude of life's tests.

3. Literature Survey

[1] The Paper Titled “Improving Skin-Disease Classification” by author T Pham published in the year 2020. It addresses the issue of class imbalance for classifying of skin diseases and suggests a hybrid method for handling it. To improve classification performance, the proposed method combines data- level and algorithm-level techniques. Additionally, fully connected layers and a customized loss function are introduced in the paper to improve the neural networks' capacity for learning. Model is assessed using evaluation measures such as accuracy, recall, precision, and standard deviation.

[2] Another paper titled “Training Deep Neural Networks on Imbalanced Data Sets” by author Shoujin Wang focuses on how well suggested loss functions work when dealing with imbalanced data sets in classification. It examines three common approaches - sampling techniques, cost-sensitive methods, and hybrid methods. Real-world data sets, such as pictures from the CIFAR-100 data set and documents from the 20 Newsgroups data set, are used for the experiments. Fmeasure and AUC metrics are used to assess the effectiveness of the suggested loss functions.

[3] The paper titled ”Evaluation of Deep Learning Systems for Skin Cancer Classification” and was published in Scientific Reports. The paper examines how well three deep learning models(ORI, BON, and BLF) classify skin cancer in comparison to dermatologists. The ISIC 2019 dataset was used by the authors to train and assess the models. After choosing the optimal model using a training and validation dataset, they assessed the model's performance using the Test-10 dataset, which comprised 10% of the ISIC 2019 dataset. Dermatologists were outperformed by the three models (ORI, BON, and BLF) in the classification of skin cancer. Dermatologists had an AUC of 67.1%, whereas the models' AUCs ranged from 91.6% to 94.4%. With AUC of 94.4%, BLF outperformed all 157 dermatologists who took part in the trial.

[4] The paper titled “Studies on Different CNN Algorithms” by author Zhe Wu discusses the use of convolutional neural networks (CNNs) for the diagnosis of facial skin diseases. It highlights the necessity of creating specific models for various body parts as well as the significance of enhancing dataset quality and network structure to raise the models' overall performance. Five distinct CNN structures were used in the studies, which demonstrated CNNs' capacity to identify conditions affecting the facial skin. But there is still room for improvement in the models' overall performance, particularly for conditions with similar clinical manifestations. According to the paper's conclusion, specific models for various body parts are needed when employing CNNs to diagnose skin conditions on the face. In order to increase the models' performance, it highlights the necessity for better datasets and network topologies. More research is still needed on the use of artificial intelligence tools in the medical field, especially in dermatology.

[5] The paper titled “Skin Cancer Detection” by author Swati Jayade discusses the method for detecting skin cancer by using support vector machines (SVM) and digital image processing. The significance of timely discovery and the difficulties posed by conventional biopsy techniques are emphasized. Compared to conventional biopsy techniques, the suggested method seeks to increase the accuracy and efficiency of skin cancer diagnosis. The use of image enhancement, segmentation, feature extraction, and SVM classification contributes to the overall effectiveness of the model.

4. Survey Comparison

Table -1: Survey of relevant research papers

Author	Techniques	Gaps
T. Pham et al. [1] [2020]	Balanced Mini-Batch Logic, CNN	Generalizability to other datasets
S. Wang et al. [2] [2016]	Synthetic Data Generation, Data Resampling, Loss Function	Possible overfitting with oversampling
C. Tri Pham et al. [3] [2020]	Customized Batch Logic, Loss Function, Deep CNN	Performance relies on training data quality and quantity,

		challenging generalization
Zhe Wu et al. [4] [2019]	Support Vector Machine (SVM), GLCM	Sensitivity to Image Quality
Swati Jayade et al. [5] [2020]	CNNs, Transfer Learning, Performance Metrics	Fine-tuning and training from scratch may require a large amount of labeled data

5. CONCLUSION

In summary, pioneering hybrid system that seamlessly combines dermoscopy and artificial intelligence to elevate the precision and efficiency of skin lesion diagnosis. Addressing the challenges associated with imbalanced datasets, here the approach integrates Synthetic Minority Over-sampling Technique (SMOTE, mini-batch logic and Augmenter during training. This combination enriches the dataset with diverse samples, mitigating classification disparities and fostering a robust multiclass skin-disease classification.

To address imbalanced datasets, the system employs SMOTE, mini-batch logic and Augmenter technique. SMOTE synthesizes minority class instances, while mini-batch logic ensures an even distribution of samples among classes. This strategic combination enhances the learning process, promoting a more equitable classification of multi-class skin diseases. DenseNet169 serves as the backbone of the Convolutional Neural Network (CNN) architecture, a model renowned for image recognition tasks. Complementing this, paper propose a customized loss function to optimize the system's multi-class skin-disease classification performance. These components collectively enhance the model's ability to extract intricate features from skin lesions.

This review highlights the comprehensive nature of the hybrid system, addressing challenges in skin lesion diagnosis. The incorporation of SMOTE, mini-batch logic, Augmenter, DenseNet169, and a customized loss function underscores commitment to advancing the field. This effort reinforces the vision for a future where early detection of skin cancer is not only feasible but a routine reality on a global scale.

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