Deep Convolutional Feature Scaling with EfficientNetB3 for Robust Early Detection of Smoking Patterns in Health Informatics

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Abstract.

With the underlying that smokers and non smokers should be given a special treatment and treatment planning, smoking is the main cause of these preventable conditions like cancer, respiratory diseases and cardiovascular diseases. It is important to detect the smoking habits at an early age to mitigate any health-related complications caused by smoking, and to enhance the overall health of the population. It uses the EfficientNetB3 network to optimize the performance of smoking detection by the state-of- the-art convolutional neural network with a balance between the model complexity and performance.

Keywords. Smoking Detection, EfficientNetB3 Model, Convolutional Neural Networks (CNN),

1. INTRODUCTION

Smoking also contributed substantially to the etiology of cancer, respiratory and cardiovascular diseases, and ranks among the top causes of preventable diseases. Quite often medical examinations presuppose that the distinction between smokers and non-smokers should be made, as this distinction will help develop particular treatment regimens and personalized care. There is a need to identify the smoking behavior among the younger age to lower the incidence of development of smoking diseases and have a positive impact on the health status of the population [1-3].

2. INPUT DATASET

To conduct this analysis, the data was gathered in the open-source Kaggle platform, which provides a diversity of sufficient images, as shown in Fig. 1. The overall data set has 3,254 confirmed image files, separated into smoking and non-smoking. They are divided into three subsets: 320 images in an extended category, 326 images in a secondary category, and 2,608 images in the main category.

(a) (b)

Fig. 1 Dataset image for (a) No - Smoking (b) Smoking image type

3. FINE-TUNED EFFICIENTNETB3 MODEL

The present work uses the EfficientNetB3 model to enhance the accuracy of the prediction of the smoking and non-smoking condition. Large-scale image weights are pre-trained into the model, which means that it can extract features. This base architecture makes the 1536-dimensional feature vectors, on which we rely our detection of characteristics in an image that are of interest as shown in Fig. 2.

Layer (type)	Output Shape	Param #
EfficientNetB3 (Functional)	(None, 1536)	10,783,535
BatchNormalization	(None, 1536)	6,144
Dense (Dense)	(None, 256)	393,472
Dropout (Dropout)	(None, 256)	0
Dense_1 (Dense)	(None, 2)	514
Total Parameters	-	11,183,665
Trainable Parameters	-	11,093,290
Non-Trainable Parameters	-	90,375

Fig. 2. Layer-wise Depiction of the proposed model

4. PROPOSED METHODOLOGY

The methodology for this study is structured into four distinct phases, each playing a crucial role in the successful prediction of smoking and non-smoking statuses using the EfficientNetB3 model.

Phase 1: Dataset Collection: The initial step is the compilation of a massive number of smoking and non-smoking medical pictures. It can be made diverse with clinical repositories and open-access tools.

Phase 2: Model Development: In this step a model (EfficientNetB3) is chosen and trained to accomplish the smoking detection jobs. The model has a potent feature extraction system that is tuned to address medical image difference.

Phase 3: Model Training and Validation: The model is also trained through an iterative optimization of the prepared dataset, which minimizes classification errors and enhances accuracy.

Phase 4: Model Evaluation and Testing: The last step tests the model using unknown test data. The accuracy, precision, recall and F1-score metrics are derived to measure the ability to predict. Ground truth labels are used to compare predictions and to determine reliability.

5. RESULTS

The EfficientNetB3 model classified the 3,254 smoking and non-smoking images with high accuracy, precision, recall and F1-score. Its stable operation focuses on its practicality in smoking detection, health studies, and early intervention uses.

A. Classification Report Analysis

The efficiency of the EfficientNetB3 model in differentiating between smoking and non-smoking images with overall accuracy of 90 indicates that the model has a high capacity to classify between smoking and non-smoking images (Fig. 3). The model had a precision of 0.90, a recall of 0.83 and an F1-score of 0.86 for the not-smoking class which showed a strong detection but slightly lower in recall than that of the smoking class.

Class	Precision	Recall	F1-Score	Support
not_smoking	0.90	0.83	0.86	126
smoking	0.90	0.94	0.92	194
Accuracy	-	-	0.90	320
Macro Avg	0.90	0.89	0.89	320
Weighted Avg	0.90	0.90	0.90	320

Fig. 3 Classification Report Analysis

B. Training and Validation loss Analysis

The Training and Validation Loss graph (Fig. 4) shows that the loss values decrease with increasing epochs of both training and validation sets. The training loss (red line) starts at a reasonably high level, but goes down fast, which means that the model fits the training data better.

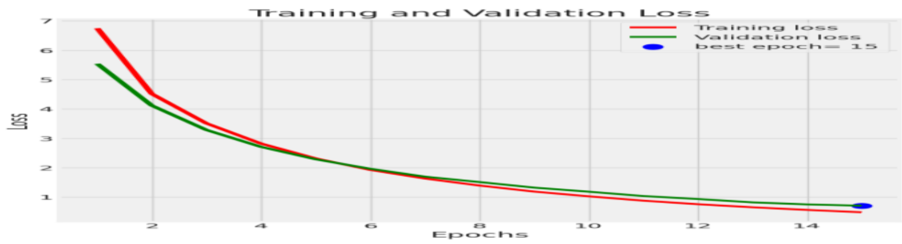

Fig. 4 Training and Validation Loss Analysis

C. Training and Validation Accuracy Analysis

The trends of the accuracy during the 15 epochs are displayed in the graph "Training and Validation Accuracy" in Fig. 5. The trend in the training accuracy, as the epochs progress, is a steadily increasing curve, approaching 100% to signify that the model is becoming progressively more competent to predict results on the training data accurately.

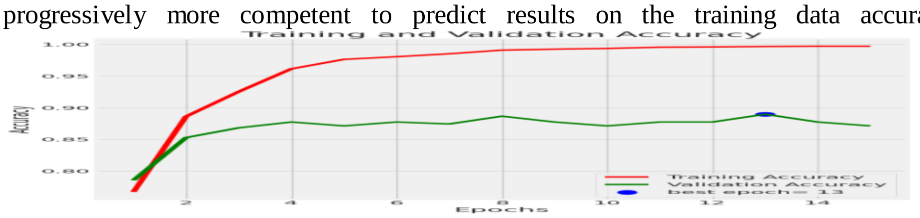

Fig. 5 Training and Validation Accuracy Analysis

D. Confusion Matrix Analysis

The confusion matrix (Fig. 6) of the EfficientNetB3 model reveals its impressive accuracy in smoking and non-smoking image classification. In the not smoking group it made 105 true positives and 21 false negatives whereas in the smoking group it made 182 true positives and just 12 false positives

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Fig. 6 Confusion Matrix Analysis

7. CONCLUSION

This paper highlights the pressing necessity to differentiate between smokers and non-smokers in order to promote individualized treatment and enhance health care planning. Since smoking is one of the major causes of preventable diseases like cancer, respiratory diseases, and cardiovascular diseases, it is important to detect smoking habits at an early stage to minimize the health risks associated with smoking and improve the health outcomes of the population.

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