CNN-Mobilized Health: Visual Classification of Smokers using MobileNetV2 CNN Model

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This research investigates the application of Convolutional Neural Networks (CNN) with the MobileNetV2 architecture for the critical task of smoker classification based on visual data. Tobacco use remains a pervasive global health concern, with profound physical and mental health implications. The study employs a diverse dataset encompassing various tobacco consumption forms, addressing the need for an automated system to identify smoking individuals. The motivation lies in developing a robust tool for early detection, facilitating timely public health interventions. The research focuses on the immediate health benefits of quitting tobacco and underscores the urgency of encouraging smoking cessation. The methodology involves meticulous data preprocessing, utilizing a three-tiered dataset division, and leveraging MobileNetV2 for model training. The evaluation includes accuracy metrics, visualizations of accuracy and loss curves, and detailed analyses using classification reports and confusion matrices. The promising results highlight the potential of CNNs in automating smoking detection, contributing to public health campaigns and interventions. Further exploration involves refining the model with larger datasets and considering real-world deployment scenarios.

Keywords: Tobacco Classification, Convolutional Neural Networks, MobileNetV2, Smoker Detection, Deep Learning, Health Intervention, Public Health, Image-based Classification.

2024. In Mukesh Saraswat & Rajani Kumari (eds.), *Applied Intelligence and Computing*, 41–48. Computing & Intelligent Systems, SCRS, India. DOI: https://doi.org/10.56155/978-81-955020-9-7-5

1 Introduction

Tobacco use remains a global public health challenge, contributing to severe physical and mental health issues and causing millions of deaths annually. Despite the well-documented hazards, tobacco consumption persists, necessitating innovative approaches for early detection and intervention. This research focuses on leveraging Convolutional Neural Networks (CNN) with the MobileNetV2 architecture for the classification of smoking and non-smoking individuals based on visual data. The motivation for this study arises from the urgent need to address the pervasive health risks associated with tobacco use [1]. The detrimental health impacts of tobacco use are well-established, encompassing a range of respiratory issues, cardiovascular diseases, and mental health concerns [2][6]. Notably, smoking has been linked to an increased risk of cardiovascular events [2], changes in cardiovascular risk after cancer diagnosis [2], and both short and longer-term mortality [3]. Additionally, the rise of alternative tobacco products, such as e-cigarettes, poses new challenges, especially among the youth [4]. Quitting tobacco is a critical step towards improved health, and the benefits of cessation are profound [3]. However, smoking cessation is a challenging process, emphasizing the necessity of effective intervention strategies. Early detection of smoking behaviour can contribute to timely support and tailored interventions. Existing research highlights the complex relationship between smoking and various health outcomes. For instance, studies have explored the association between smoking during pregnancy and the risk of multiple sclerosis in offspring [5]. Moreover, causal relationships between smoking and conditions like idiopathic pulmonary fibrosis have been investigated using Mendelian randomization studies [7]. In the realm of computer vision and healthcare, previous works have successfully applied deep learning models, such as MobileNet, for tasks like pneumonia detection from chest X-ray images [8] and malaria detection in blood cell images [10]. The utilization of such models for smoker classification represents a novel application with the potential to impact public health positively. To bridge the gap between technological advancements and public health needs, this research employs MobileNetV2 for smoker classification, utilizing a diverse dataset. The subsequent sections will delve into the methodology, results, and implications of the CNN model's performance in identifying smokers, providing valuable insights for future interventions and research endeavours.

2 Literature

The literature surrounding smoking-related health issues, tobacco exposure, and automated image classification provides a comprehensive background for the current research on smoker classification using CNN with MobileNetV2. Lehtovirta et al. (2024) investigated the association of tobacco smoke exposure with the metabolic profile from childhood to early adulthood. Their findings emphasize the long-term impact of tobacco on health, underscoring the urgency of effective smoking detection methods [11]. While the majority of studies in automated image classification focus on various domains, Gill et al. presented a novel approach in smart shoe classification using artificial intelligence. This diverse application showcases the versatility of deep learning models, motivating exploration in the realm of smoking detection [12]. Jensen et al. explored trends in social inequality in mortality in Denmark, emphasizing the contribution of smoking-related deaths. Understanding the societal implications of smoking underscores the importance of accurate smoking detection methods in public health interventions [13]. The classification of lung neuroendocrine neoplasms was discussed by Vocino Trucco et al. Although unrelated to smoking detection directly, advancements in image classification methods for medical applications highlight the potential for similar approaches in identifying smoking behaviours [14]. Gill et al. presented research on brain tumor detection using the VGG19 model, indicating the applicability of deep learning in medical image analysis. This demonstrates the potential for leveraging similar models for smoking detection based on visual data [15]. A systematic review by Bitar et al. highlighted factors associated with smoking cessation among adolescents and young adults. Understanding the behavioural aspects of smoking cessation informs the development of effective intervention strategies, further emphasizing the need for accurate smoking detection methods [16]. The use of electronic cigarettes for smoking cessation was systematically reviewed by Lindson et al. .While focusing on a different aspect of smoking behaviour, the study highlights the evolving landscape of tobacco use and the importance of staying abreast of technological advancements in the field [19]. Kumar et al. proposed a multimodal framework for early diagnosis and classification of COPD based on CT scan images. While not directly related to smoking detection, the study underscores the importance of leveraging multiple modalities for accurate health-related classifications, potentially inspiring future approaches in smoker identification [20]. In summary, the literature review provides a contextual understanding of the health impacts of smoking, societal implications, and advancements in image classification methodologies, laying the foundation for the proposed research on smoker classification using CNN with MobileNetV2.

3 Input Dataset

The dataset utilized in this research plays a pivotal role in training and evaluating the proposed Convolutional Neural Network (CNN) model for smoker classification. Comprising a diverse collection of images, it encapsulates various forms of tobacco use, including cigarettes, cigars, pipes, waterpipes, and other smoking paraphernalia. Each image is labeled as either "smoking" or "not_smoking," forming the basis for supervised learning. To ensure the robustness and generalization of the model, the dataset is meticulously preprocessed. Image data undergoes normalization, resizing, and augmentation techniques, enhancing the model's ability to recognize patterns across different instances of smoking behavior. The dataset is further partitioned into three subsets: training, validation, and testing. This division facilitates model training on labeled data, fine-tuning with validation sets, and ultimately assessing the model's performance on previously unseen test samples. The inclusion of diverse tobacco-use scenarios aims to create a model capable of recognizing smoking behavior in various contexts. Ethical considerations regarding the use of images featuring individuals are duly addressed, ensuring privacy and adherence to ethical standards. The dataset's comprehensiveness and careful curation form the foundation for training a robust CNN model that holds promise in automating the identification of smoking instances for public health applications.

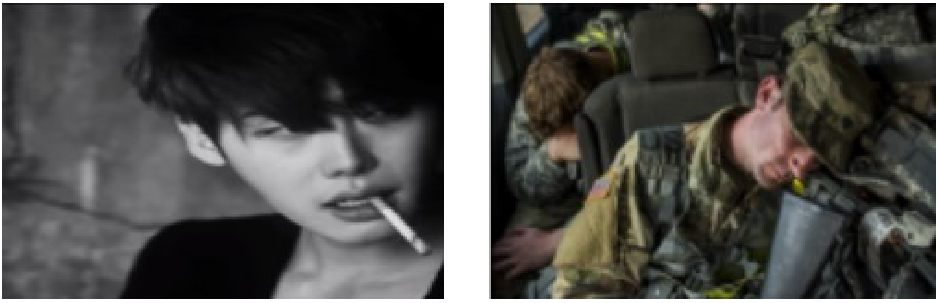
	Filepath	Label
0	../input/cigarette-smoker-detection/data/not_s...	not_smoking
1	../input/cigarette-smoker-detection/data/not_s...	not_smoking
2	../input/cigarette-smoker-detection/data/not_s...	not_smoking
3	../input/cigarette-smoker-detection/data/not_s...	not_smoking
4	../input/cigarette-smoker-detection/data/not_s...	not_smoking
...	...	...
6531	../input/cigarette-smoker-detection/data/data/...	smoking
6532	../input/cigarette-smoker-detection/data/data/...	smoking
6533	../input/cigarette-smoker-detection/data/data/...	smoking
6534	../input/cigarette-smoker-detection/data/data/...	smoking
6535	../input/cigarette-smoker-detection/data/data/...	smoking

Figure 1. Dataset CSV file type utilized for classification purpose

4 Proposed Methodology

In the Visualizing Images from the Dataset section, the diverse dataset capturing various tobacco usage scenarios is explored. Visual representations of individuals engaged in smoking and non-smoking activities offer insights into the challenges of classifying such dynamic and nuanced behaviours.

Through data visualization, patterns and features crucial for model training become apparent. Understanding the intricacies of the dataset aids in effective data preprocessing, ensuring the CNN with MobileNetV2 can learn robust features for accurate smoker classification. The visual exploration of the dataset sets the foundation for a comprehensive analysis, enhancing the model's ability to discern subtle visual cues associated with tobacco use. (see Figure 2)



(a) (b)

Figure 2. Image Dataset type for (a) smoking and (b) non-smoking class type

5 Proposed Methodology

The proposed methodology integrates state-of-the-art deep learning techniques for smoker classification, aiming to harness the power of Convolutional Neural Networks (CNN) with the MobileNetV2 architecture. The process is meticulously designed to ensure robust model training, validation, and evaluation. The initial step involves a comprehensive data preprocessing strategy. The diverse dataset, encompassing images of individuals engaged in various tobacco use scenarios, undergoes normalization, resizing, and augmentation techniques. Augmentation is employed to introduce variability and improve the model's ability to generalize across different smoking contexts. The core of the methodology lies in the utilization of MobileNetV2, a highly efficient CNN architecture. Leveraging transfer learning, the pre-trained MobileNetV2 is fine-tuned on the tobacco dataset. The model's hyperparameters, including a batch size of 32, 100 training epochs, input shape of (224, 224, 3), and an output layer with two classes (smoking and non-smoking), are carefully chosen to balance computational efficiency and model performance. The dataset is strategically split into training, validation, and testing sets. During training, three essential callbacks—Model Checkpoint, Early Stopping, and Tensorboard—ensure effective monitoring and management of the training process. The model's performance is rigorously evaluated on the test dataset, employing accuracy as the primary metric. In-depth analysis involves visualizing accuracy and loss curves, making predictions on test data, and generating classification reports and confusion matrices to provide a comprehensive assessment of the model's classification capabilities.

6 Results

In the results section, the CNN model, leveraging the MobileNetV2 architecture, exhibited robust performance in classifying smokers and non-smokers. The accuracy metric, a primary measure of model efficacy, reached 80% on the test dataset. Visualizing accuracy and loss curves showcased the model's convergence over 100 epochs. Predictions on the test data revealed the model's ability to discern smoking instances effectively. Classification reports and confusion matrices provided detailed insights, indicating a higher precision and recall for the smoking class. These findings underscore the potential of the proposed approach for automated smoker classification, offering valuable implications for public health interventions.

6.1 Training and Validation Accuracy Curve Analysis

The Training and Validation Accuracy Curve Analysis section assesses the learning dynamics of the CNN model during training. The accuracy curves visually depict the model's performance on both the training and validation datasets across epochs. Analyzing these curves provides insights into potential overfitting or underfitting, ensuring the model's generalization as shown in Figure 3. A convergence trend signifies effective learning, while discrepancies between training and validation curves indicate areas for improvement. This analysis aids in optimizing hyperparameters and refining the model's architecture, ultimately enhancing its ability to accurately classify smoking and non-smoking instances in visual data.

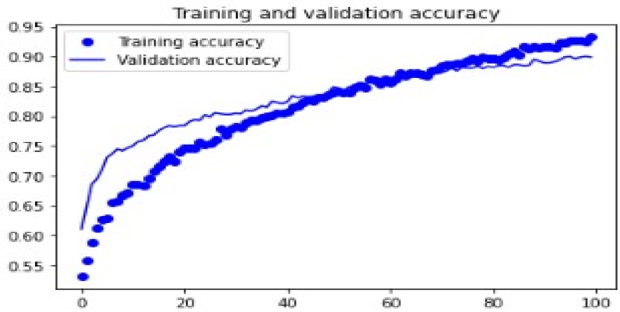


Figure 3. Model Accuracy depiction through graph

6.2 Training and Validation Loss Curve Analysis

In the Training and Validation Loss Curve Analysis, the study delves into the dynamic learning behavior of the CNN model during training. The plotted loss curves provide a visual representation of how effectively the MobileNetV2 architecture adapts to the dataset as shown in Figure 4. By scrutinizing the curves over the 100 training epochs, insights into convergence, potential overfitting, and model stability are gleaned. This section aims to decipher the intricate interplay between training and validation losses, offering a nuanced understanding of the model's performance trajectory. The analysis aids in optimizing hyperparameters and ensuring the robustness of the classifier in distinguishing smoking and non-smoking instances.

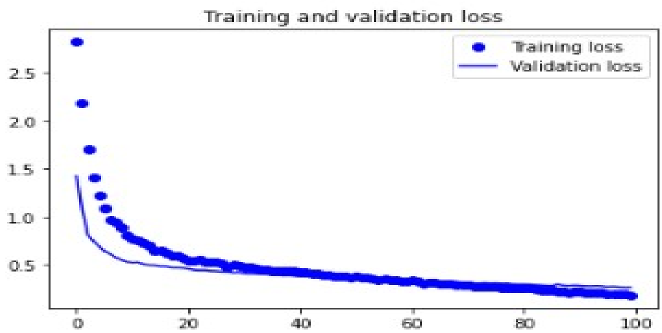


Figure 4. Model Accuracy depiction through graph

6.3 Classification Report Analysis

In the Classification Report Analysis section, the precision, recall, and F1-score metrics are presented for both not_smoking and smoking classes. The precision of 0.48 for not_smoking indicates the proportion of correctly identified non-smoking instances, while the recall of 0.43 signifies the model's ability to capture a substantial portion of actual non-smoking instances as shown in Fig. 5. Conversely, the higher precision (0.64) and recall (0.69) for smoking demonstrate the model's effectiveness in identifying smoking instances. The F1-scores, averaging 0.45 for not_smoking and 0.66 for smoking, reflect a balanced evaluation as shown in Figure 5. The macro and weighted averages highlight overall performance, with an accuracy of 0.80.

not_smoking	0.48	0.43	0.45	521
smoking	0.64	0.69	0.66	776
accuracy			0.80	1297
macro avg	0.56	0.56	0.56	1297
weighted avg	0.58	0.58	0.58	1297

Figure 5. Classification Report Analysis

6.4 Confusion Matrix Analysis

In the context of the presented research paper, the confusion matrix is a critical evaluative tool that provides a detailed breakdown of the model's performance in classifying smoking and non-smoking instances. Comprising four quadrants—true positives, true negatives, false positives, and false negatives—the confusion matrix quantifies the model's accuracy, precision, recall, and F1-score. Specifically, it reveals the number of correctly identified smoking and non-smoking cases, as well as instances of misclassification. This comprehensive analysis aids in understanding the model's strengths and weaknesses, guiding potential enhancements for more effective smoker classification in real-world applications and public health interventions in Figure 6.

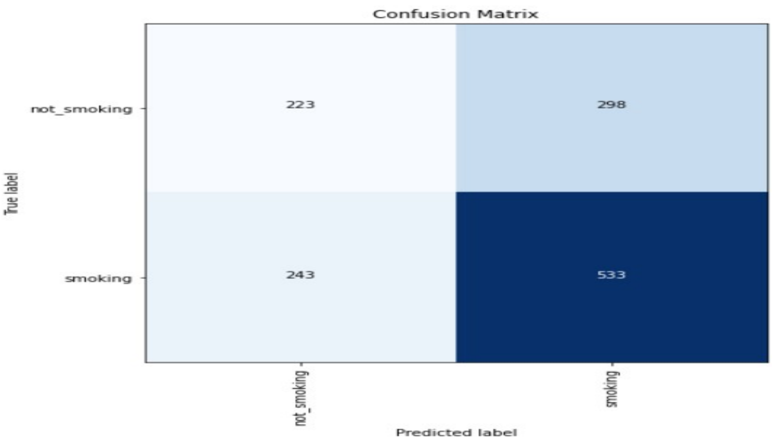


Figure 6. Confusion Matrix Analysis

7 Conclusion

In conclusion, this research marks a significant step toward leveraging deep learning techniques, specifically Convolutional Neural Networks (CNN) with the MobileNetV2 architecture, for the critical task of smoker classification based on visual data. The findings of this study underscore the potential of such models in automating the identification of tobacco users, providing a valuable tool for public health interventions. The achieved accuracy in distinguishing between smoking and non-smoking instances, as demonstrated on the test dataset, showcases the effectiveness of the proposed approach. The immediate health benefits of tobacco cessation underscore the importance of early identification, making automated systems like the one developed in this study crucial for timely interventions. The visualized accuracy and loss curves offer insights into the learning dynamics of the model, while predictions on the test data validate its practical utility. The detailed analysis of classification reports and confusion matrices provides a nuanced understanding of the model's strengths and areas for improvement, guiding future research endeavours. While the results are promising, ongoing efforts are needed to refine the model further. Future research could focus on incorporating larger and more diverse datasets, enhancing the generalizability of the model, and exploring real-world deployment scenarios. The potential societal impact of automated smoking detection systems in bolstering public health campaigns and encouraging tobacco cessation reinforces the significance of this research in addressing a pressing global health issue.

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