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Predicting Asthma Attacks Through AI-Powered Thermal Imaging Analysis of Breathing Patterns

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***Abstract*—Breathing patterns understanding plays a crucial role in assessing human health, notably in the early detection and prediction of asthma attacks. Identifying these patterns, including inhalation and exhalation, is essential for doctors. However, the current methods, such as invasive techniques like belts or nasal probes, often cause considerable discomfort to patients. Given the rapid advancements in artificial intelligence (AI) and computer vision, there is a pressing need to leverage these technologies for developing non-invasive diagnostic solutions. Leveraging the precision of AI, this study introduces an innovative asthma attack prediction model employing contactless thermal imaging to evaluate asthma severity. By meticulously analyzing thermal patterns emanating from the nasal area, our model promises a groundbreaking shift in asthma diagnostics. Validation on a robust benchmark dataset collected at the University of Technology Malaysia showcased exceptional performance metrics, with accuracy, precision, recall, and F1-score each reaching an unprecedented 99.49%, 98.01%, 98.4%, and 99.2% respectively. Beyond its high accuracy, this method emphasizes patient comfort and accessibility, potentially democratizing asthma management across varied healthcare settings. This research not only underscores the feasibility of non-invasive asthma assessment but also sets a precedent for future explorations in leveraging computer vision for respiratory condition diagnostics.**

***Index Terms*—Asthma attack prediction, Transfer learning, Thermal images, VGG16, Inhale, Exhale.**

I. Introduction

Severe asthma attacks, also known as exacerbation, can have profound and distressing impacts on individuals, significantly affecting their quality of life [1], [2]. These attacks are characterized by sudden and intense worsening of asthma symptoms, including shortness of breath, wheezing, coughing, and tightness in the chest. Such episodes can be frightening, as they may quickly escalate to respiratory distress and even life-threatening conditions if not managed promptly and effectively [3], [4]. The severity and unpredictability of these attacks often lead to increased hospital visits and admissions, imposing substantial healthcare burdens. Beyond the physical symptoms, severe asthma exacerbation can lead to psychological effects such as anxiety and depression, driven by the fear of future attacks and the frustration of living with a chronic condition that limits everyday activities [5], [6]. The unpredictability can affect employment and educational opportunities, leading to economic stress and reduced overall well-being. Thus, managing severe asthma and preventing exacerbation through appropriate medication, lifestyle adjustments, and regular monitoring is crucial to mitigate these impacts and improve the quality of life for those affected [7], [8].

Inhale and exhale breath analysis is gaining prominence as a valuable non-invasive approach to diagnosing a range of health conditions [9]. This method can assess both general well-being and specific diseases without resorting to invasive diagnostic procedures [10]. The pattern of breathing serves as a crucial indicator of an individual's health status, offering valuable insights into their overall physiological condition. Various diseases, such as asthma attacks, lung cancer, and pulmonary hypertension, are directly linked to breathing [11], [12]. Specifically, asthma profoundly impacts the respiratory system, resulting in significant breathing disturbances. In response to this challenge, researchers have endeavored to develop innovative solutions utilizing Artificial Intelligence (AI). These endeavors aim to empower healthcare professionals to predict diseases without resorting to uncomfortable invasive methods, thus enabling timely intervention and optimal patient care.

AI can be defined as software capable of analyzing, understanding, and reacting to input in a manner resembling human performance [13], [14]. This technology has been increasingly utilized in the medical field to aid doctors in the diagnosis of various diseases, including skin cancer [15], breast cancer [16], thyroid cancer [17], Parkinson [18] and COVID-19 [19], revolutionizing medical diagnostics and improving patient outcomes, where Machine Learning (ML) [20], considered one of the most powerful AI tools, and it has several effective types such as Convolutional Neural Networks (CNN), Deep Neural Networks (DNN). ML, in turn, has been extensively investigated to assist doctors in the medical field, particularly in tasks like Medical Image Classification (MIC) [21]. While ML methods such as Decision Trees (DT) [22], Support Vector Machines (SVMs) [23], and k-nearest neighbors (KNN) [24] have been applied in MIC for a significant period, their effectiveness has been hindered by various limitations. These include subpar performance compared to practical standards and a slow pace of development progress in recent years. Over the last few years, many studies have been conducted using different Machine Learning (ML) methods to tackle asthma

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attacks. Kilic et al. [25], Developing a lightweight architecture for asthma detection using cough sounds, achieving high accuracy with robust cross-validation. sarkar et al. [26], present a non-invasive method for asthma detection using single-lead electrocardiogram (ECG), achieving high accuracy rates through Complete Ensemble Empirical Mode Decomposition with Adaptive Noise(CEEMDAN) and Principal Component Analysis (PCA) for ECG Derived Respiration (EDR) extraction. Alhamad et al. [27], introduced the Internet of Medical Things (IoMT) based model for remote monitoring of chronic diseases, focusing on asthma prediction in older adults, utilizing machine learning algorithms and Internet of Things (IoT) data management for early detection. He et al. [28], Compared five ML algorithms - Logistic Regression (LR), Random Fores (RF), eXtreme Gradient Boost, Decision Tree (DT), and SVM for predicting childhood asthma, tuning hyperparameters via grid search and utilizing ensemble methods to enhance predictive performance. Bhat et al. [29], present a smartphone-based asthma risk prediction tool using ML, correlating indoor Particulate Matter (PM) and weather data with Peak Expiratory Flow Rates (PEFR) via CNN architecture, outperforming existing DNN methods architecture, outperforming existing DNN methods and offering a cost-effective IoT solution for asthma attack prediction.

Building upon prior discussions and the author's understanding, there is a noticeable scarcity of studies dedicated to predicting asthma attacks through thermography or thermal imaging, which is widely used in the medical field as a non-invasive diagnostic method. In this regard, this paper proposes a method to predict asthma attacks through thermal imaging based on the analysis of breathing patterns (inhale and exhale), aiming to assist doctors in swiftly predicting these conditions and avoiding invasive methods. These patterns are detected using thermal images, which can identify abnormal temperature changes around the nose. Analyzing the inhale and exhale patterns is crucial in predicting asthma attacks. Additionally, to distinguish which class is related to inhale or exhale, the classification of these classes is necessary. Consequently, binary classification of inspiration and expiration classes is performed using well-known pre-trained models including VGG16, Inception v3, MobileNet, ResNet101, and InceptionResNetV2. To assess the models' performance, several metrics are employed including recall, specificity, and precision. The results of classification using the dataset reveal promising accuracy, reaching up to 99%. The main contributions of the work are summarized as follows:

- Introduces a novel approach utilizing thermal imaging to analyze breathing patterns for predicting asthma attacks.
- Aims to assist doctors in swift asthma attack prediction, reducing reliance on invasive diagnostic methods.
- Successful binary classification with pre-trained models yields promising accuracy rates up to 99%

The organization of the paper is summarized as follows. Section. II presents various methods employed in the study including the proposed method and dataset employed.Section. III, introduce the results of classification along with metrics employed in the study. Section. IV, presents the

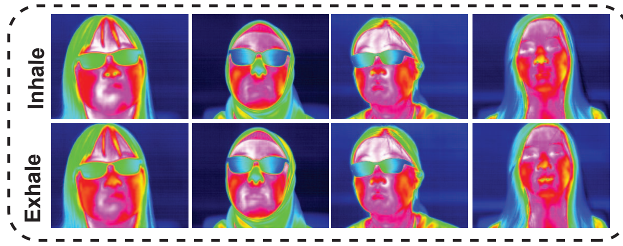

Fig. 1: Samples from the dataset used in the study.

conclusion that summarizes the work presented.

II. Proposed method

This section aims to present the proposed method for constructing an effective classification model. In Subsection II-A, we offer a comprehensive description of the dataset. Furthermore, Subsection II-B elucidates the rationale behind employing data augmentation and showcases samples post-application of this technique. Subsection II-C succinctly outlines the transfer learning process, along with the pre-trained model utilized in the study.

A. Dataset

The dataset, annotated using vision annotation tools, comprises two distinct classes. It encompasses a total of 2100 images, with 902 images attributed to the 'Inhale' class and 1192 images assigned to the 'Exhale' class [30]. Fig. 1 depicts the two class samples.

B. Data augmentation

In this subsection, we provide a rationale for the utilization of data augmentation, which involves generating new samples from existing ones. This process is instrumental in fortifying the model against overfitting, a common pitfall observed in datasets characterized by significant class imbalances—a prevalent issue in the medical domain, as underscored by our dataset. As previously outlined, our dataset comprises two classes: Inhale and Exhale, with the former containing 902 images and the latter housing 1192 images. There exists a notable class imbalance, compounded by the unlabeled nature of the data. To address this, we implemented data augmentation specifically for the Inhale class post-training. This encompassed various augmentation strategies, such as rotation and scaling, shifting to augment the dataset and enhance the robustness of the model. An example of augmented data is depicted in Fig. 2.

C. Transfer learning

To attain satisfactory performance with CNN models, substantial computational resources and vast datasets are typically necessary. Nonetheless, transfer learning (TL) serves as a valuable technique to enhance model effectiveness and reduce training duration, particularly when dealing with limited data and hardware resources. CNN architectures are assembled by

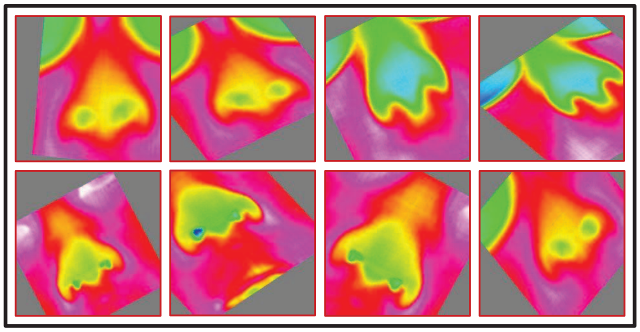

Fig. 2: Inhale class after data augmentation and ROI extraction.

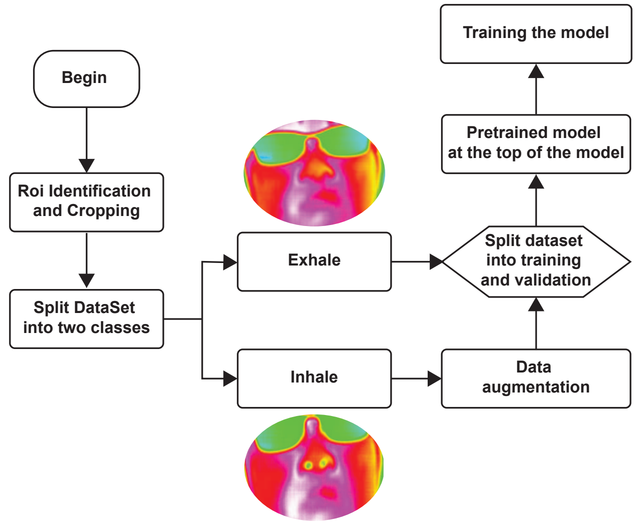

Fig. 3: Complete flowchart of the workflow.

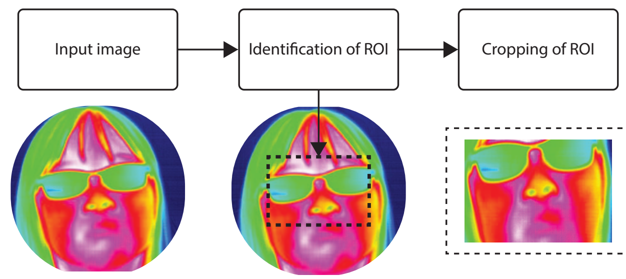

Fig. 4: The ROI identification process.

combining various deep learning layers, encompassing input, convolutional, pooling, fully connected, and output layers. Transfer learning involves the use of pre-trained convolutional neural networks (CNNs), such as those trained on ImageNet, to categorize images from various domains. Fine-tuning these pre-trained CNNs on specific datasets aids in faster convergence and acquisition of domain-specific characteristics, retaining the original network architecture while adjusting pre-trained weights to grasp task-specific attributes. Recent research has demonstrated the efficacy of fine-tuning for tasks like medical image classification. In this study, we explore fine-tuning five well-known pre-trained CNN architectures—VGG16, MobileNet, Inception-V3, ResNet101, and InceptionResNetV2—to classify breathing patterns based on thermal image modality. For instance, ResNet101 employs a residual learning framework, simplifying optimization and enabling deeper networks for enhanced performance, while Inception-V3 utilizes factorized inception modules, allowing adaptation of kernel sizes across convolution layers to learn both low-level and high-level features.

The VGG16 architecture underwent modification by substituting its final 5 layers with an average global pooling layer, followed by a single fully connected layer. The sigmoid classifier generates probabilities for the two classes of interest per patch, which serves as input during the fine-tuning phase. The training utilized the Adam optimizer, employing a consistent batch size of 32 for both training and validation. An optimal learning rate of 0.001 was determined. The training concluded after 40 epochs, indicating the network's saturation point. This fine-tuning methodology was replicated across all other networks, maintaining uniform optimization parameters. Fig. 3 illustrates a flowchart summarizing the classification process. It begins with the identification of the Region of Interest (ROI) described in Fig. 4 around the noise. Subsequently, the dataset is partitioned into two distinct classes: Inhale and Exhale, as the initially received dataset was unsegmented. Notably, a pivotal step known as data augmentation was employed specifically for the Inhale class, aimed at enriching the dataset with diverse variations. Following this, the dataset was further divided into training and validation sets. These sets were then utilized to feed pre-trained networks, enabling accurate classification of breathing pattern classes and facilitating the selection of the best-performing model based on classification performance.

III. Results and Discussion

This section is bifurcated into two subsections. The first subsection delineates the various metrics employed to assess the models' performance during the classification process. The second subsection delves into the discussion of the results derived from said classification. Notably, the experimental results were trained and tested on Google Colab, leveraging computational resources featuring an Intel Core i3 processor and 12GB of RAM.

A. Evaluation metrics

This section presents the results of the binary classification of different metrics This section presents details related to various metrics utilized to assess the model including Accuracy, Precision, Sensitivity (recall), and F1-Score. Accuracy can be defined as the proportion of correctly predicted classes compared to the total number of classifications. It is mathematically represented as:

In the context of binary classification, accuracy can be computed by considering true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

Here, TP represents the correctly classified positive images, TN represents the correctly classified negative images, FP represents the wrongly classified positive images, and FN represents the wrongly classified negative images.

Higher accuracy indicates better model performance as it provides an estimation of the probability of correct predictions.

B. Discussion

Table I provides a comprehensive overview of the performance parameters across various pre-trained models. Sensitivity (recall), specificity, precision, and F1 score are crucial metrics in evaluating the effectiveness of classification models. Among the models evaluated, MobileNet stands out with high scores across all metrics, particularly in sensitivity and precision. This indicates MobileNet's robust ability to accurately classify respiratory phases, making it a promising candidate for respiratory health monitoring applications. On the other hand, ResNet101 shows comparatively lower scores, suggesting potential limitations in its performance, particularly in correctly identifying respiratory phases.

TABLE I: Overall performance parameters

Category	Sensitivity (recall)	Specificity	Precision	F1 score
VGG16	99.37%	97.59%	99.36%	98.46%
Inception v3	99.49%	97.98%	98.01%	98.75%
MobileNet	99.39%	98.1%	98.4%	99.2%
ResNet101	93.28%	89.09%	85.26%	89.09%
InceptionResNetV2	96.64%	95.01%	98.71%	97.66%

Tab. II, which presents the classification report for each class (Exhale and Inhale) of the pre-trained models, we gain further insights into their performance characteristics. Precision reflects the model's ability to correctly classify instances of a class among all instances classified as that class, while recall measures the model's ability to correctly identify all instances of a class. F1-score, which is the harmonic mean of precision and recall, provides a balanced assessment of a model's performance. Across all models, we observe consistently high precision, recall, and F1-score for both the Exhale and Inhale classes. This indicates the models' capability to accurately distinguish between respiratory phases, highlighting their potential utility in clinical settings for respiratory health monitoring and diagnosis. Furthermore, Table III showcases the thermal image classification accuracy results, which provide insights into the models' performance in differentiating between breathing patterns. The high accuracy scores attained by MobileNet, Inception v3, and VGG16 underscore their effectiveness in accurately classifying thermal images corresponding to different breathing patterns. However, it's worth noting the relatively lower accuracy score obtained by ResNet101, indicating potential challenges in accurately classifying thermal images using this model.

TABLE II: Classification report of various pre-trained models

Model	Class	Precision	Recall	F1-Score
VGG16	Exhale	0.98	0.99	0.98
	Inhale	0.99	0.98	0.98
Inception v3	Exhale	0.99	0.98	0.99
	Inhale	0.98	0.99	0.99
MobileNet	Exhale	0.99	0.99	0.99
	Inhale	0.99	0.99	0.99
ResNet101	Exhale	0.93	0.84	0.88
	Inhale	0.85	0.93	0.89
InceptionResNetV2	Exhale	0.97	0.99	0.98
	Inhale	0.99	0.97	0.98

TABLE III: Thermal image classification accuracy results

Models	Training 85% & Testing 15%
VGG16	97.81%
Inception v3	98.74%
MobileNet	99.49%
ResNet101	88.58%
InceptionResNetV2	97.69%

All in all, the pre-trained models evaluated in this study demonstrate promising performance in simulating asthma attacks through thermal imaging. MobileNet emerges as a particularly strong contender, exhibiting high accuracy and robust performance across various performance metrics. These findings hold significant implications for respiratory health monitoring and diagnosis, highlighting the potential of deep learning models in enhancing the prediction capabilities of asthma attacks by correctly classifying respiratory patterns.

IV. Conclusion

This paper presents a comprehensive exploration of utilizing thermal imaging coupled with advanced deep-learning techniques for the non-invasive prediction and assessment of asthma attacks. By leveraging a novel classification model that incorporates transfer learning and data augmentation, we have successfully demonstrated the potential of thermal images to provide valuable insights into respiratory conditions, particularly asthma. The model's emphasis on analyzing thermal patterns around the nasal region during the inspiration and expiration phases has yielded decent accuracy, precision, and F1-score metrics, each reaching 99.49%, 98.4%, and 99.2%. These results highlight the model's efficacy in distinguishing between different respiratory. The findings of this study represent a promising avenue for enhancing asthma management. By providing a non-invasive, accurate, and comfortable method for patients. Furthermore, this work lays a solid foundation for future research aimed at expanding the applications of thermal imaging and deep learning in diagnosing and monitoring other respiratory conditions. In future works, it is imperative to continue exploring these innovative approaches, with a focus on refining algorithms, enhancing model performance, and validating findings across larger and more diverse datasets that we will collect in the UAE to solidify the role of AI in respiratory healthcare.

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