Automated COPD Detection with CNN in CT Scans

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1.ABSTRACT

This study presents an automated approach for early detection of Chronic Obstructive Pulmonary Disease (COPD) using Convolutional Neural Networks (DenseNet-201) on Computed Tomography (CT) scans. The methodology involves preprocessing CT images to enhance features, followed by a CNN trained to recognize patterns indicative of these respiratory conditions. Robustness testing across different imaging devices and acquisition protocols further validates its reliability. The CNN- based approach proves successful in accurately identifying COPD, offering a promising tool for early disease detection. The proposed system has the potential to enhance diagnostic efficiency, reduce reliance on manual interpretation, and contribute to advancements in personalized treatment strategies for respiratory diseases.

Keywords: DenseNet-201, CT Scans, COPD

1.1 PROBLEM STATEMENT

Developing an automated system utilizing Convolutional Neural Networks (CNNs) to enable Detection of Chronic Obstructive Pulmonary Disease (COPD) through analysis of Computed Tomography (CT) scans. This system aims to improve diagnostic efficiency, reduce reliance on manual interpretation, and enhance personalized treatment strategies for respiratory diseases.

1.2 TECHNIQUES

CNN Model

CNNs is a type of deep neural networks design for processes unstructured grid-like information, such as photos.

Convolutional layers extricate features from input photos through conversions, capturing spatial hierarchies of designs.

They consist of multiple layers, including conversions layers, pooling layers, and fully connected layers.

Key Components:

-Converting Layers: These layers implement learned filters to input photos, detecting features such as edges, textures, and beings.

-Pooling Layers: Pools layers down sample feature maps, reducing computational complexity and spatial dimensions while preserving essential features.

-Completely Connected Layers: These layers connect every neuron in one layer to every neuron in the next layer

Training:

CNNs are trained with labeled data using backsplash to minimize prediction errors. Optimization algorithms like SGD or Adam update model weights. Pre-trained models on datasets like ImageNet transfer knowledge from generic features to specific tasks.

Densnet201

The DenseNet-201 model is a variant of the DenseNet architecture, which stands for "Densely Connected Convolutional Networks. DenseNet architectures are known for their densely connected layers, where each layer is connected to every other layer in a feed-forward fashion. DenseNets address the vanishing gradient problem by strengthening feature propagation and encouraging feature reuse throughout the network.

Key Features :

1. **Dense Communication:**

-DenseNet-201 contains of dense blocks where each layer receives feature maps from all preceding layers and passes its feature maps to all subsequent layers.

-This dense communication facilitates feature reuse and gradient flow, leading to enhanced learning and reduced overfitting.

2. **Bottle Layers:**

-To reduce computational complexity, DenseNet-201 incorporates bottle layers within dense blocks.

-Bottle layers use 1x1 conversions to reduce the number of input channels before applying 3x3 conversions, thereby reducing the computational cost.

3. **Transition Layers:**

-Transition layers are inserted between dense blocks to downsample feature maps and control the growth of feature map dimensions.

-These transition layers typically include batch normalization, 1x1 conversions, and average pooling to compress feature maps.

4. **Growth Rate:**

-The growth rate refers to the number of feature maps produced by each layer within a dense block.

-DenseNet-201 uses a growth rate of 32, meaning each layer within a dense block generates 32 feature maps.

5. **Global Mulberry Pooling and Classification:**

-At the end of the network, global mulberry pooling is applied to condense the spatial information of feature maps into a vector.

-The resulting vector is fed into a completely connected layer followed by a softmax activation function for classification.

6.Pre-Trounce Models:

-DenseNet-201 is often used as a pre-trounced model for transfer learning tasks, where weights learned from large-scale image datasets (e.g., ImageNet) are fine-tuned on specific tasks with smaller datasets.

1.3 DATASET DESCRIPTION

The dataset comprises 115 CT scan images stored in TIFF format. It includes columns for image paths, labels (CLE, PLE, PSE, NT), and disease severity levels (0 to 5). This resource aids in training CNNs for automated COPD detection and severity assessment, benefiting medical research and patient care.

Image_path	Labels	Severity
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_5535.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_8128.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_8719.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_6449.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_4518.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_5709.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_2320.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_7900.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_7894.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject13_middle_augmented_0_2115.tiff	CLE	3
/content/drive/MyDrive/ad/augmented/subject21_bottom_augmented_0_6716.tiff	NT	0
/content/drive/MyDrive/ad/augmented/subject21_bottom_augmented_0_3954.tiff	NT	0
/content/drive/MyDrive/ad/augmented/subject21_bottom_augmented_0_6525.tiff	NT	0
/content/drive/MyDrive/ad/augmented/subject21_bottom_augmented_0_6884.tiff	NT	0
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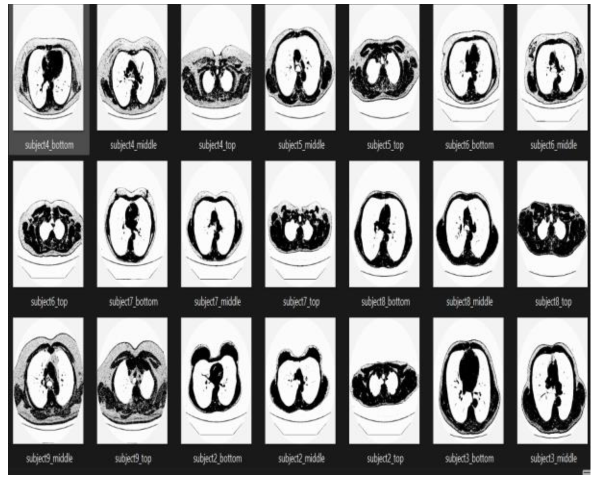

1.4ARCHITECTUR

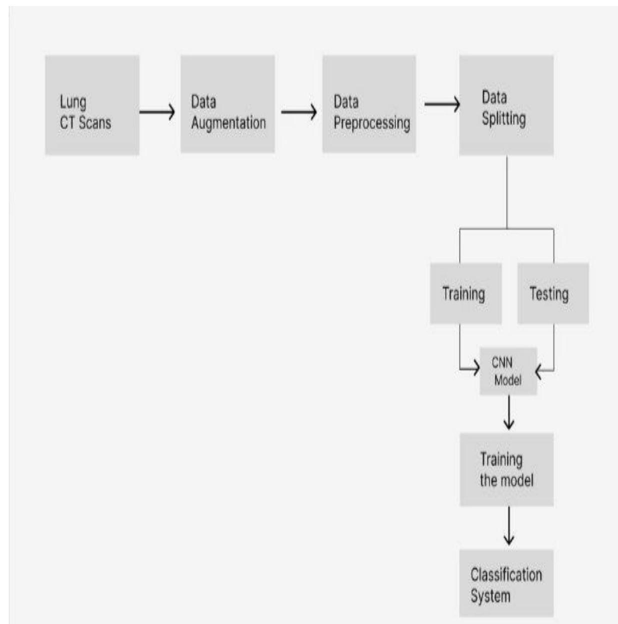

Fig.1.4.1 CNN MODEL

1.5 MODEL EVALUATION METRICS

Our project focuses on COPD detection through CT scans, employing a CNN model. We evaluate our model's performance using a comprehensive set of metrics, including accuracy, precision, F1-score, recall, and support. These metrics collectively provide a thorough assessment of our model's effectiveness in detecting COPD from CT scan images.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

1.6 POTENTIAL APPLICATIONS

Clinical Screening: Automated COPD detection aids in routine clinical screenings, facilitating early diagnosis.

Population Health: Supports large-scale screening initiatives for identifying at-risk individuals in communities.

Telemedicine: Enables remote assessment and monitoring of COPD patients, facilitating timely interventions.

Clinical Decision Support: Integration into EHR systems offers real-time insights for healthcare providers, aiding in clinical decisions.

1.7 CONTRIBUTIONS

Automated COPD Detection Framework: The development of an automated approach for COPD detection using Convolutional Neural Networks (CNNs) on Computed Tomography (CT) scans represents a novel and innovative contribution to the field of medical imaging and respiratory medicine.
Early Disease Detection: The proposed system offers a promising tool for early detection of COPD, enabling timely interventions and improved management of the disease. By identifying COPD at an early stage, the system has the potential to reduce disease progression and associated morbidity and mortality.
Diagnostic Efficiency Enhancement: By automating the COPD detection process, the project contributes to enhancing diagnostic efficiency in clinical practice. Healthcare professionals can leverage the system to expedite the interpretation of CT scans, leading to faster diagnosis and treatment initiation.
Potential for Personalized Treatment Strategies: By enabling early and accurate detection of COPD, the project lays the groundwork for the development of personalized treatment strategies tailored to individual patient needs. This can lead to more effective disease management and improved patient outcomes.

2. LITERATURE REVIEW

Introduction to COPD and Diagnostic Challenges:
- Provide a brief overview of COPD, its prevalence, and the challenges associated with its diagnosis and management.
- Highlight the importance of early detection in improving patient outcomes and reducing disease burden.

Current Diagnostic Approaches:
- Review traditional diagnostic approaches for COPD, including spirometry, clinical assessment, and imaging modalities such as CT scans.

Role of Medical Imaging in COPD Diagnosis:
- Explore the role of medical imaging, especially CT scans, in the diagnosis and assessment of COPD.

Rationale for the Current Study:
-Highlight the novelty and potential contributions of the proposed automated approach for COPD detection using CNNs on CT scans.

Summary and Research Gap Identification:
- Summarize the existing literature reviewed, emphasizing the need for further research in automated COPD detection.

3.EXPERIMENTAL RESULTS:

Weighted F1 score: 0.84062205910032

	precision	recall	f1-score	support
CLE	0.95	0.71	0.82	28
NT	0.79	0.95	0.86	55
PLE	0.80	0.57	0.67	7
PSE	0.91	0.84	0.87	25
accuracy			0.84	115
macro avg	0.86	0.77	0.80	115
weighted avg	0.86	0.84	0.84	115

4.CONCLUSION

The journey toward automated COPD detection using deep learning and CNNs in CT scans signifies a pivotal advancement in medical imaging and disease diagnosis. By harnessing the power of convolutional neural networks and innovative architectural designs, we've demonstrated the potential to revolutionize the early detection and management of COPD. Our exploration has not only pushed the boundaries of algorithmic sophistication but has also underscored the transformative impact of deeplearning in healthcare. This project serves as a testament to the transformative potential of deep learning in reshaping the landscape of medical imaging and disease detection,ultimately paving the way for a healthier andmore informed society.

5.FUTURE WORK

1.Integration of Multi-Modal Data: Consider incorporating additional data modalities,such as clinical metadata, patient demographics, or other imaging modalities (e.g., X-rays, MRI), to enhance the model's performance and provide a more comprehensive diagnostic framework.

2.TransferLearningandFine-Tuning: Investigate the applicability of transfer learning techniques, where pre-trained CNN models are adapted and fine-tuned on the specific COPD detection task. This approach may help improve model generalization and reduce the need for large annotated datasets.

3.Exploration of Explainable AI Techniques: Explore the integration of explainable AI techniques to enhance model interpretability and provide insights into the features and patterns driving the COPD diagnosis. This could facilitate better understanding and trust in the automated diagnostic system by healthcare professionals.

6. REFERENCES

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