Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

# Cough Based Lung Infection Detection Using Deep Learning

**N. Lavanya, B. Gowri Priya, G. Sai Prasad, A. Sai Theja**

[1]*Assistant Professor*

*Department Of Computer Science and Engineering*

[2]*Department Of Computer Science*

*and Engineering B. Tech, 4th Year Student*

[3]*Department Of Computer Science and Engineering*

*B. Tech, 4th Year Student*

[4]*Department Of Computer Scienceand Engineering*

*B. Tech, 4th Year Student*

***Abstract***

Pulmonary infections are a major global health concern that can result in a significant number of fatalities annually, regardless of age. Early diagnosis of lung disorders is essential to enable medical professionals to treat the afflicted individual. Many deep learning algorithms have been utilized in current systems to identify lung illnesses from cough sounds, but the results have not proven very accurate. This work presents a novel deep learning algorithm-based method for the early identification of lung infections using cough sounds. The suggested system uses the deep learning algorithm, RESNET-18, to analyze and categorize cough sounds. By listening to a person's cough sounds, it is possible to determine whether or not they may have a lung disease, such as pneumonia, pulmonary edema, asthma, TB, COVID19, pertussis, or another respiratory illness. It offers a safe and economical way to determine the likelihood of lung infections.

***Keywords:*** *Respiratory illness diagnosis, cough-based diagnosis, deep learning algorithms, Feature extraction, Audio processing, ResNet-18 algorithm.*

**Introduction**

As a global health concern, respiratory disorders necessitate prompt identification. This work investigates the use of the deep learning algorithm ResNet-18 to analyze cough noises in order to diagnose lung infections, offering a safe alternative to harmful diagnostic techniques. Pulmonary disorders range from mild illness to life-threatening infections, and prompt diagnosis is essential for appropriate treatment. The traditional method has patients see medical experts, which causes diagnostic delays, higher expenses, and restricted access in impoverished areas. Conventional approaches for diagnosing lung disorders sometimes entail intrusive techniques, such X-rays and other testing, which might not be feasible in all situations. The advent of deep learning methods, particularly convolutional neural networks (CNNs), presents an opportunity for the creation of effective and painless diagnostic instruments.

**Deep Learning:** Deep learning is an artificial intelligence (AI) technique that trains computers to interpret information in a manner similar to that of the human brain. To provide precise predictions, deep learning models are able to identify intricate patterns in images, text, audio, and other types of data.

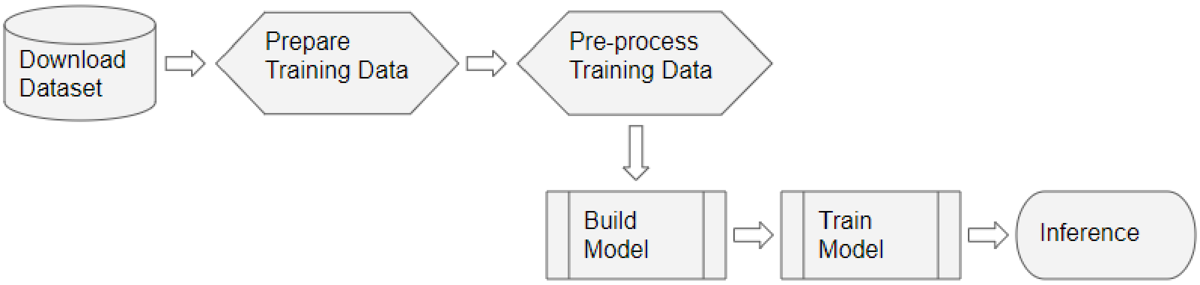


**Fig 1:Deep Learning Workflow**

**ResNet-18:** A CNN architectural type that is a member of the ResNet (Residual Networks) family is called ResNet-18. The usage of residual blocks is the main innovation of ResNet. Shortcut (or skip) connections that evade one or more tiers are included in residual blocks. This facilitates training very deep networks by enabling the network to learn residual functions. The vanishing gradient problem is made easier by the residual connections, which also aid in the training of deeper neural networks.

**Audio Classification**: Consider this application as the "Hello World" of audio deep learning, just as the MNIST dataset classification of handwritten digits is the first "Hello World" task for computer vision. Beginning with sound recordings, we will transform them into spectrograms, feed the resulting data into a CNN + Linear Classifier model, and generate predictions on the class of sound.

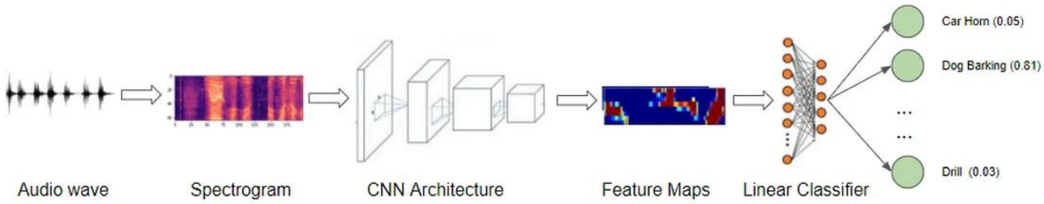


**Fig 2: Audio Classification application**

**Literature Review**

The paper "Estimation of Respiratory Rate from Breathing Audio" [1] outlines a machine learning technique that use spectrogram representation of audio signals and tagged data for breathing cycles. They are able to obtain a Mean Absolute Error (MAE) of 1.0 by estimating respiratory rate solely from auditory data by training a recurrent neural network to recognize these cycles. To address the lack of publicly available datasets, they propose a unique data augmentation approach that expands the effective size of the accessible dataset. This augmentation method makes use of the periodic frequency components of the spectrogram to generate several signal representations. With the use of volume datasets, the study [4] "Lung Diseases Detection Using Various Deep Learning Algorithms" presented a method to identify and categorize several lung illnesses, including pneumonia, TB, and lung cancer, using X-ray and Computerized Tomography (CT) scan pictures. They trained three deep learning models—the sequential, functional, and transfer models—by putting them into practice. Their models were able to achieve greater degrees of accuracy for potential fixes, offer humanity efficacy for quicker illness identification, and function as the top models. In terms of an F1 score of 98.55%, accuracy of 98.43%, recall of 96.33% for pneumonia, and for TB F1 score of 97.99%, accuracy of 99.4%, and recall of 98.88%, the findings showed that the suggested framework with a sequential model works better than other current techniques. Furthermore, the cancer functional model surpassed current pretrained models with a 99.9% accuracy and a 99.89% specificity. It also allows for a reduced number of trained parameters, which reduces computing overhead and costs. Researchers Jordi Laguarta, Ferran Hueto, and Brian Subirana developed an AI speech processing framework in their study [5] "COVID-19 Artificial Intelligence Diagnosis Using Only Cough Recordings." This framework uses acoustic biomarker feature extractors to pre-screen for COVID-19 from cough recordings and provide a personalized patient saliency map for longitudinal patient monitoring in real-time, non-invasively, and at nearly zero variable cost. Mel Frequency Cepstral Coefficient is used to convert cough recordings, which are then fed into a Convolutional Neural Network (CNN) architecture consisting of three parallelly trained ResNet50s and one Poisson biomarker layer. The result is a binary pre-screening diagnosis. Our CNN-based models were evaluated on the remaining 1064 patients in our dataset after being trained on 4256 participants. By using transfer learning to learn biomarker features on bigger datasets, which we have successfully done in our lab on Alzheimer's, our architecture's COVID-19 discriminating accuracy is greatly improved.

**Proposed System**

This technology uses cough sounds to identify lung illnesses by utilizing deep learning and cutting edge technologies. The technology allows users to upload cough audio recordings via a web interface. After processing the provided audio, a Mel spectrogram is produced. This is then sent to a neural network model (ResNet-18) that has already been trained for prediction. A webpage showcasing the outcomes includes a pie chart that illustrates the probability of both positive and negative predictions.

**ADVANTAGES**

• The smart tool's rapid screening feature enables timely diagnosis of lung infections, enabling people to take the appropriate treatment right away.

• The system analyzes cough sounds in an effort to discover lung infections early.
•The analysis of cough noises is automated through the use of a deep learning algorithm (ResNet-18), which makes the procedure reliable and quick. The algorithm gains accuracy in recognizing patterns associated with lung infections by learning from a dataset.

**Methodology**

**Data Collection**

We gather cough sounds from a variety of sources, such as people who have lung infections and a control group of healthy people, in order to compile an extensive dataset. Gathering information from diverse sources and people makes it easier to distinguish between cough sounds related to different respiratory ailments. The deep learning model uses the gathered data as training data.

**Preprocessing**

The preprocessed data is transformed into a spectrogram, which is a graphic depiction of the intensity of cough sounds over time at different frequencies. The neural network (ResNet-18) is trained using the characteristics extracted from audio data via the spectrogram. Filter banks and the Short-Time Fourier Transform (STFT) are used to transform audio input into spectrograms. In order to facilitate efficient deep learning analysis, this preprocessing of the acquired data is done to eliminate noise and undesired information.

**ResNet-18 Architecture**

The ResNet-18 architecture was chosen due to its acknowledged effectiveness in classifying tasks including images and audio. With its residual blocks, ResNet-18 is a deep convolutional neural network that may be used to train deeper networks and address problems such as disappearing gradients. This architecture has been taught to analyze spectrograms of cough sounds:

• ***Input Layer:*** Cough noises' frequency and temporal characteristics are recorded using spectrograms, which are used as inputs.
• ***Convolutional Layers:*** To capture structured characteristics in the spectrogram, many convolutional layers with tiny filter sizes are employed.
• ***Residual Blocks:*** One distinctive aspect of ResNet design is the presence of residual blocks. Because skip connections are present in every block, the input can bypass one or more levels. As a result, the network's information flow is made simpler, which enables the model to identify many patterns linked to lung infections.
• ***Global Average Pooling:*** This technique is used to extract key characteristics for classification and compress

the spatial dimensions.

• ***Fully Connected Layers:*** The last layers provide the chance of having a lung infection and finish the classification using the learnt characteristics.

**Training the Model**

There are three sets of the dataset: training, validation, and testing. Utilizing an appropriate optimization approach, the model is trained. To avoid overfitting, the model's performance is monitored on the validation set throughout training. Several measures are used to gauge the model's efficiency, including as accuracy, precision, and recall. To determine how excellent the suggested strategy is, comparisons with other approaches are made. Cross-validation procedures are taken into consideration to guarantee the robustness of the model's performance in various data subclasses.

**System Architecture**

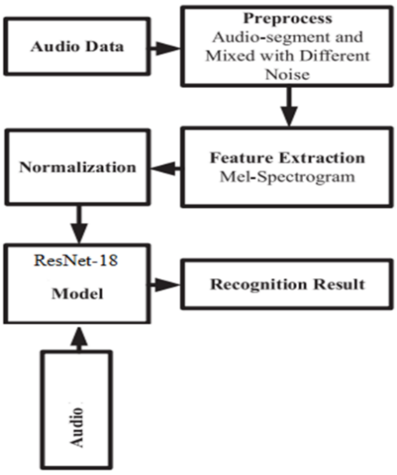


**Fig 3: System Architecture**

**RESULTS :**

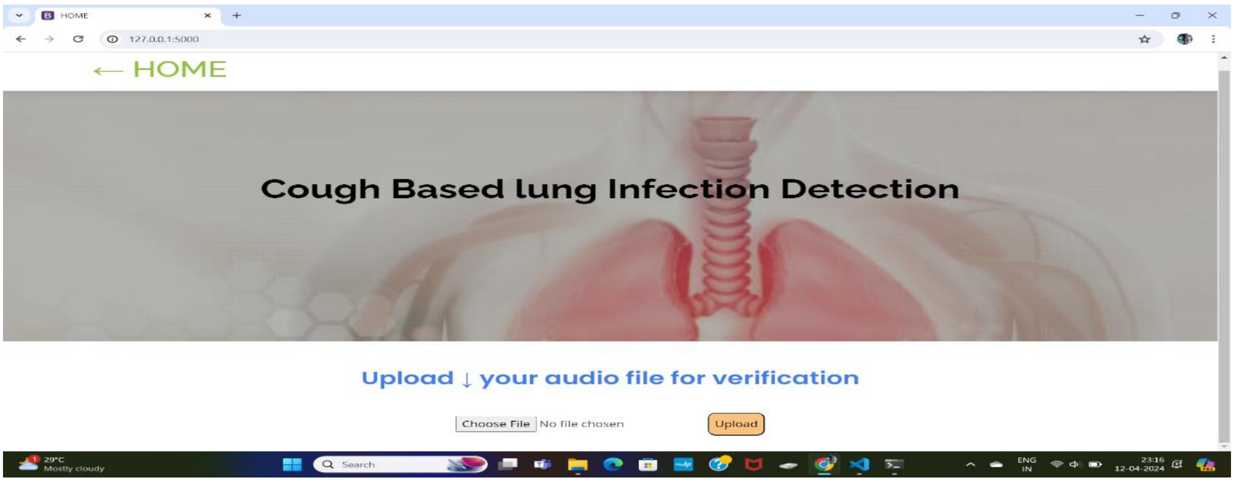


**Fig 4: Home Page**

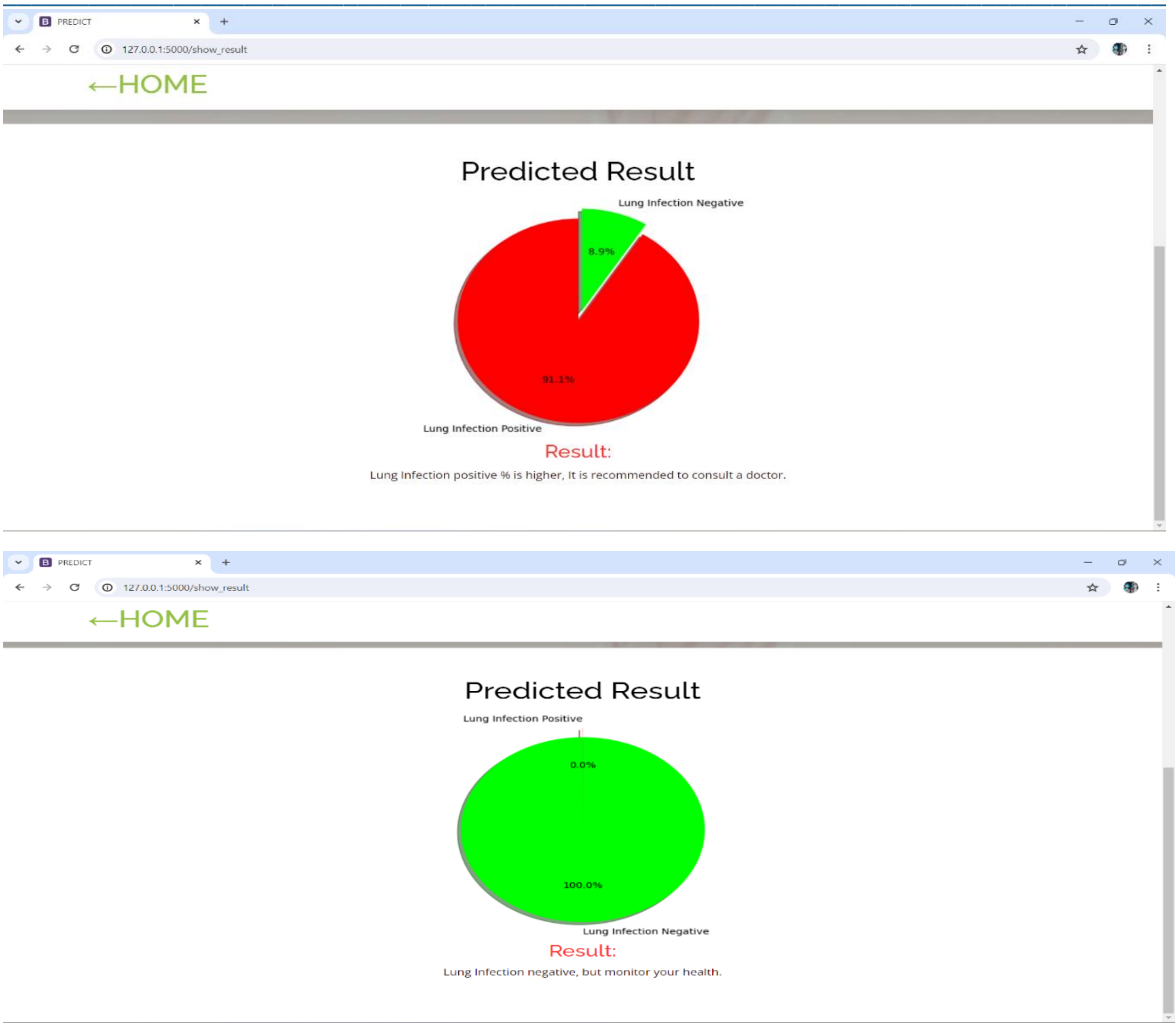


**Fig 5: Predicting lunge Infection**

## Conclusion

To sum up, the application of deep learning to the examination of cough audio data signifies a significant shift in the way lung infection diagnoses are made. This technique provides a new solution to the problems associated with conventional diagnostic processes thanks to its user-friendly online interface, ResNet-based prediction model, and Mel spectrogram synthesis. This invention has the potential to change the landscape of lung health diagnostics by reducing time and expense, enhancing approachability, and offering a painless substitute. This concept is an example of advancement as healthcare and technology are now combining. This strategy has the potential to enhance patient outcomes and lessen the global burden of respiratory illnesses. A persistent dedication to thorough validation, ethical concerns, and cooperative efforts across multidisciplinary domains are necessary on the route to substantial therapeutic effect. Enhancing the ResNet-18 modal continuously, looking for alternative topologies, and combining data from many modalities might increase lung infection detection's reliability and accuracy.

## Future Scope

Future research will employ a multifaceted approach that incorporates advancements in technology, a continuous improvement in diagnostic capacities, and international cooperation. The strategy may develop into a thorough and vital instrument in the field of respiratory health by being at the forefront of research and technology, benefiting patients, medical professionals, and the healthcare ecosystem as a whole.

**References**

[1] J. Harvill, Y. Wani, Mustafa Alam, Narendra Ahuja, M. Hasegawa-Johnsor, David Chestek, David G Beiser, (2022). Estimation Of Respiratory Rate From Breathing Audio DOI: 10.1109/EMBC48229.2022.9871897

[2] Kumar, A., Abhishek, K., Chakraborty, C., & Kryvinska, N. (2021). Deep Learning And Internet Of Things Based Lung Ailment Recognition Through Coughing Spectrograms DOI: 10.1109/access.2021.3094132

[3] G. Augustinov, P. Fischer, Volker Gross, Ulrich Koehler, K. Sohrabi, and Seyed Amir Hossein Tabatabaei. (2020). Automatic Detection And Classification Of Cough Events Based On Deep Learning. https://doi.org/10.1515/cdbme-2020-3083

[4] M. Jasmine Pemeena Priyadarsini, Ketan kotecha, G. K. Rajini, K. Hariharan, K. Utkarsh Raj, K. Bhargav Ram, V. Indragandhi ,V. Subramaniyaswamy, and Sharnil Pandya. (2023). Lung Diseases Detection Using Various Deep Learning Algorithms. https://doi.org/10.1155/2023/3563696

[5] Laguarta, J., Hueto, F., & Subirana, B. (2020). COVID-19 Artificial Intelligence Diagnosis using only Cough Recordings. IEEE Open Journal of Engineering in Medicine and Biology, doi:10.1109/ojemb.2020.3026928.

[6] Tracey, B. H., Comina, G., Larson, S., Bravard, M., Lopez, J. W., & Gilman, R. H. (2011). Cough detection algorithm for monitoring patient recovery from pulmonary tuberculosis. 2011. doi:10.1109/iembs.2011.6091487

[7] Infante, C., Chamberlain, D., Fletcher, R., Thorat, Y., & Kodgule, R. (2017). Use of cough sounds for diagnosis and screening of pulmonary disease. 2017 IEEE Global Humanitarian Technology(GHTC). doi:10.1109/ghtc.2017.8239338.

[8] Sharan, R. V., Abeyratne, U. R., Swarnkar, V. R., & Porter, P. (2017). Cough sound analysis for diagnosing croup in pediatric patients using biologically inspired features. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). doi:10.1109/embc.2017.8037875

[9] Botha, G. H. R., Theron, G., Warren, R. M., Klopper, M., Dheda, K., van Helden, P. D., & Niesler, T. R. (2018). Detection of tuberculosis by automatic cough sound analysis. Physiological Measurement, 39(4), 045005. doi:10.1088/1361-6579/aab6d0

[10] Ramesh, V., Vatanparvar, K., Nemati, E., Nathan, V., Rahman, M. M., & Kuang, J. (2020). *CoughGAN:* Generating Synthetic Coughs that Improve Respiratory Disease Classification*. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). doi:10.1109/embc44109.2020.917559

[11] Md. Nahiduzzaman, Md. Omaer Faruq Goni, Md. Shamim Anower (Member, Ieee), Julfikar Haider, Saravanakumar Gurusamy (Member, Ieee), Rakibul Hassan, And Md. Rakibul Islam.(2021). A Novel Method For Multivariant Pneumonia Classification Based On Hybrid CNN-PCA Based Feature Extraction Using Extreme Learning Machine With CXR Images. DOI: 10.1109/ACCESS.2021.3123782

[12] Sharan, R. V., Berkovsky, S., Navarro, D. F., Xiong, H., & Jaffe, A. (2021). Detecting pertussis in the pediatric population using respiratory sound events and CNN. Biomedical Signal Processing and Control, 68, 102722. doi:10.1016/j.bspc.2021.102722

[13] Coppini, G., Diciotti, S., Falchini, M., Villari, N., & Valli, G. (2003). Neural networks for computer-aided diagnosis: detection of lung nodules in chest radiograms. IEEE Transactions on Information Technology in Biomedicine, 7(4), 344–357. doi:10.1109/titb.2003.821313

[14] Basu, V., & Rana, S. (2020). Respiratory diseases recognition through respiratory sound with the help of deep neural network. 2020 4th International Conference on Computational Intelligence and Networks (CINE). doi:10.1109/cine48825.2020.234388

[15] Pham, L., McLoughlin, I., Phan, H., Tran, M., Nguyen, T., & Palaniappan, R. (2020). Robust Deep Learning Framework For Predicting Respiratory Anomalies and Diseases. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). doi:10.1109/embc44109.2020.9175704.