Lung Tumor Segmentation Using Visual Geometry Group Networks In Mri Images

Mrs.M.Geethalakshmi[1], Nithish S[2], Nithish S[3],Gokul k[4]

[1, 2, 3]Dept of Electronics and Communication Engineering

[1, 2, 3, 4] kongunadu College of Engineering and Technology,

Tiruchirapalli,Tamilnadu,India

Abstract- *Lung cancer is one of the most life-threatening diseases worldwide, and early diagnosis significantly increases the chances of survival. Accurate detection and classification of lung tumors remain challenging due to variations in tumor size, shape, and texture in MRI images. This study proposes an automated lung tumor segmentation and classification framework using Convolutional Neural Networks (CNN) and the Visual Geometry Group (VGG) network architecture. The proposed system utilizes MRI images to analyze textural and spatial features of lung tissues for distinguishing between normal and malignant cases. A multi-scale feature extraction approach is incorporated to improve detection performance and enhance classification accuracy. The VGG network serves as the base model for deep feature learning, while CNN layers refine segmentation and classification tasks. The developed database includes multiple MRI views to ensure robust training and validation. Experimental results demonstrate that the proposed model achieves high precision and overall classification accuracy of up to 98%, as evaluated using confusion matrix metrics. The system reduces manual interpretation errors and provides an efficient computer-aided diagnostic tool for early lung tumor prediction.*

Keywords: Lung cancer (Bronchogenic Carcinoma) detection,VGG-16,Image classification, Convolutional neural networks

I. INTRODUCTION

Lung cancer is defined as the abnormal and uncontrolled growth of cells in the human lung and remains one of the leading causes of cancer-related mortality worldwide. It accounts for more deaths annually than breast, prostate, and colon cancers combined. Major risk factors include cigarette smoking, exposure to carcinogenic environments such as radioactive gases and air pollution, and genetic predisposition. Based on severity, lung cancer is categorized into different grades, with Grades I and II considered lower grade and Grades III and IV indicating higher malignancy and aggressiveness. Early and accurate diagnosis is essential for effective treatment and improved survival rates.Medical diagnosis commonly relies on imaging techniques such as CT, ultrasound, and MRI scans, along with pathological examinations like biopsy. Among these, imaging modalities provide high-resolution visualization of lung tissues, enabling three-dimensional assessment of lesions. However, manual interpretation of medical images may lead to misdiagnosis due to variability in tumor appearance and complexity.

To address these challenges, this study proposes an automated lung tumor segmentation and prediction system using Convolutional Neural Networks (CNN) and the Visual Geometry Group (VGG) network architecture on MRI images. Deep learning, a subset of machine learning based on multi-layer neural networks, enables automatic extraction of complex features from medical images without extensive manual preprocessing. The VGG network is utilized for deep feature extraction, while CNN layers perform accurate classification of normal and malignant lung tissues. Unlike region-based approaches such as RCNN, the proposed framework focuses on a VGG-based CNN architecture for efficient segmentation and prediction.

Lung Cancer Segementation

Pulmonary tumors are considered one of the most lethal diseases worldwide. Lung cancer is primarily caused by the irregular and uncontrolled proliferation of lung tissue cells, with smoking being one of the major contributing factors. Environmental pollution and genetic predisposition also increase the risk of developing the disease. According to global health statistics reported by organizations such as the World Health Organization, lung cancer remains one of the leading causes of cancer-related deaths among both men and women. Early prediction of lung cancer significantly improves the chances of successful treatment and patient survival.

Medical imaging plays a vital role in clinical assessment, and MRI images provide detailed visualization of soft tissues without radiation exposure. However, manual interpretation of MRI scans may lead to diagnostic variability. To address this issue, this study proposes a lung cancer prediction system using Convolutional Neural Networks (CNN) integrated with the Visual Geometry Group (VGG)

architecture. The proposed method focuses only on prediction and classification of lung tumors from MRI images and does not employ RCNN-based detection techniques.

II. LITERATUREREVIEW

Recent advancements in deep learning have significantly improved lung cancer prediction and classification from medical images.

[1] Shariff, V., Paritala, C., and Ankala, K. M. (2025) proposed an optimized framework for non-small cell lung cancer detection using Convolutional Neural Networks (CNN) with differential data augmentation techniques, published in Scientific Reports. Their study focused on improving model generalization and robustness by applying advanced augmentation strategies to overcome data imbalance and limited dataset challenges. The results demonstrated improved classification accuracy and stability, highlighting the importance of preprocessing and augmentation in enhancing CNN-based medical image prediction systems.

[2] Ozdemir, B., Aslan, E., and Pacal, I. (2025) proposed an Attention-Enhanced InceptionNeXt-based hybrid deep learning model for lung cancer detection. Their study integrates attention mechanisms with the InceptionNeXt architecture to improve feature representation and focus on the most relevant regions of lung images. By combining multi-scale feature extraction with attention modules, the model enhances discriminative capability and reduces the influence of irrelevant background information.

[3] Ur Rehman, Zia et al. (2024) proposed an effective lung nodule detection framework using a deep Convolutional Neural Network (CNN) integrated with dual attention mechanisms, published in Scientific Reports. The study focuses on enhancing lung nodule identification by incorporating both spatial and channel attention modules within the CNN architecture. These dual attention mechanisms enable the network to concentrate on the most informative regions and relevant feature maps, thereby improving the discriminative capability of the model.

The proposed approach addresses challenges such as variability in nodule size, shape, and texture by enabling adaptive feature refinement during training. By emphasizing critical image regions and suppressing irrelevant background information, the model achieves improved sensitivity and overall accuracy. Experimental validation demonstrated superior performance compared to conventional CNN-based methods, particularly in reducing false positives and improving detection robustness.

This work highlights the effectiveness of attention enhanced deep learning architectures in medical image analysis and underscores the importance ofadvanced feature learning strategies for improving lung cancer diagnosis systems.

[4] Gautam, N., Basu, A., and Sarkar, R. (2024) proposed a lung cancer detection framework using an ensemble of deep learning models, published in Neural Computing and Applications. Their study focuses on improving diagnostic accuracy from thoracic MRI scans by combining multiple deep learning architectures rather than relying on a single model.

The ensemble approach integrates predictions from different convolutional neural network (CNN) models to enhance robustness and generalization. By aggregating complementary features learned by diverse networks, the system reduces overfitting and improves sensitivity and specificity in lung cancer detection. The authors conducted extensive experiments on thoracic MRI datasets, demonstrating that the ensemble model outperforms individual deep learning classifiers in terms of accuracy and reliability.

This research highlights the effectiveness of ensemble strategies in medical image analysis, emphasizing that combining multiple deep learning models can significantly enhance lung cancer diagnosis performance and support clinical decision-making.

[5] Shahadat, Nazmul, Lama, Ritika, and Nguyen, Anna (2024) proposed a deep AI-based model for lung and colon cancer detection, published in Cancers. Their study developed a robust deep learning framework capable of automatically extracting high-level features from medical images for accurate cancer classification. The proposed AI model was trained to distinguish between normal and malignant tissue patterns, demonstrating strong performance in both lung and colon cancer datasets.

The research emphasized the effectiveness of convolutional neural networks (CNN) in learning complex image representations without manual feature engineering. Through extensive experimentation, the model achieved high classification accuracy and improved generalization capability. The study highlights the potential of deep AI systems in supporting early cancer diagnosis and reducing dependency on manual interpretation, thereby enhancing clinical decision-making processes.

III. PROBLEMIDENTIFICATION&OBJECTIVES

3.1 Problem Statement

Lung cancer is one of the leading causes of cancer-related mortality worldwide, and early prediction plays a critical role in improving patient survival rates. Accurate analysis of lung tumors using MRI images remains a challenging task due to variations in tumor size, shape, intensity, and texture. Manual examination of MRI scans by radiologists is time-consuming and may lead to diagnostic variability or misclassification, especially in early-stage tumors. Therefore, there is a need for an automated and reliable lung tumor prediction system that can assist clinicians in making accurate decisions.

3.2 Existing Methodology

Exploration In the existing system, medical imaging plays a crucial role in the diagnosis and evaluation of lung cancer. Common imaging modalities include chest radiography (X-ray), Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and radionuclide bone scanning. Among these, CT imaging is most widely used due to its high sensitivity in detecting tumor size, shape, location, and lymph node metastasis. Although X-ray imaging can identify larger lung tumors, CT scans provide more detailed cross-sectional images, enabling better visualization of abnormalities. Efficient lung segmentation techniques further enhance the accuracy and confidence level of abnormality identification systems.

However, the existing system still faces several limitations. In many cases, the prediction results are not sufficiently accurate, indicating the need for further optimization of algorithms and model parameters. Priority-based segmentation and precise feature extraction are required to improve classification performance. Additionally, the available database is often limited in size and diversity, which restricts the model's ability to generalize across different patient populations. Expanding the dataset to include more cases and various lung-related diseases is essential to increase robustness and reliability.

Misclassification may occur due to multiple factors. Variations in symptoms caused by smoking habits, environmental exposure, and genetic differences can affect tumor appearance in imaging data. Insufficient training samples and incomplete feature optimization may also reduce prediction performance. More comprehensive training patterns are needed to accurately capture the complex characteristics of real world lung cancer cases.Computer-Aided Diagnosis (CAD) systems are increasingly used as supportive tools for radiologists. These systems analyze nodules, lesions, and tumors using computer vision and machine learning techniques to estimate malignancy probability. CAD acts as a second reader, helping to reduce radiologist workload, fatigue, and variability in interpretation. With the growing volume of medical imaging data, automated systems are becoming essential in radiology to improve diagnostic efficiency, consistency, and early-stage lung cancer prediction accuracy.

3.3 Proposed Methodology

We used VGG-16 to predict lung cancer using MRI images. The working of the model is divided into two main phases: Feature Extraction Phase and Classification Phase. The proposed method does not use RCNN; it relies only on CNN with a VGG-16 architecture for lung tumor segmentation and prediction.

3.3.1 Data Preprocessing

Image preprocessing is a convenient technique to refine the standards of scans and upgrade them for examination andfor additional conversion. Geometric transformations of images like rotation, scaling, translationare doneinthis phase.

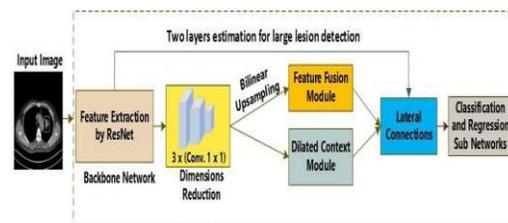**Fig-1:DataPreprocessingTechniques**

Lung Tumor Segmentation Using Visual Geometry Group Networks in MRI Images, data preprocessing plays a crucial role in improving model performance and prediction accuracy. Initially, lung MRI images are collected and properly labeled as normal or malignant to support supervised learning. All images are resized to a fixed dimension of 224 × 224 pixels to match the input requirement of the VGG-16 architecture. Pixel intensity values are then normalized to a range between 0 and 1 to ensure faster convergence and stable training of the CNN model.

To enhance image quality, noise removal techniques such as Gaussian or median filtering are applied to eliminate unwanted distortions. Contrast enhancement methods, including histogram equalization or CLAHE, are used to improve tumor visibility and highlight subtle abnormalities in

lung tissues applied to remove irrelevant background regions and focus the model only on the area of interest.
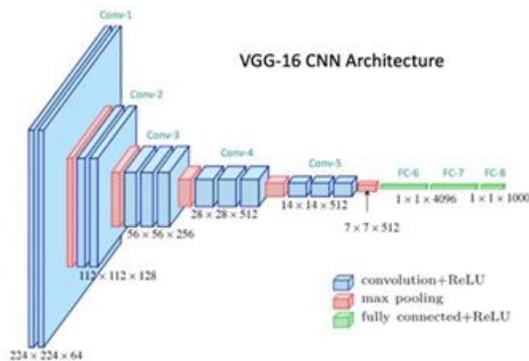
3.3.2VGG Architecture

Fig-2:VGG-16Architecture

The Visual Geometry Group (VGG) architecture is a deep Convolutional Neural Network (CNN) model known for its simple and uniform structure, which uses small 3×3 convolutional filters throughout the network. In this research on Lung Tumor Segmentation Using Visual Geometry Group Networks in MRI Images, the VGG-16 model is employed for effective feature extraction and prediction. The architecture consists of multiple stacked convolutional layers followed by ReLU activation functions and max-pooling layers for dimensionality reduction. The repeated use of small filters enables the network to capture fine-grained spatial and textural details from MRI lung images, which are essential for identifying tumor-related patterns.

VGG-16 contains 13 convolutional layers and 3 fully connected layers, making a total of 16 weight layers. The convolutional layers extract hierarchical features, where early layers detect low-level features such as edges and textures, and deeper layers learn high-level representations such as tumor shape and abnormal tissue structures. After feature extraction, the fully connected layers perform classification, and a Softmax activation function is used in the final layer to predict whether the MRI image corresponds to normal or malignant lung tissue. The simplicity, depth, and strong feature learning capability of VGG make it highly suitable for lung cancer prediction tasks without the need for region-based detection methods like RCNN.

One of the key strengths of VGG-16 is its ability to learn hierarchical feature representations. In the context of lung MRI images, the early convolutional layers capture low-level features such as edges, contours, and texture variations. The intermediate layers detect more complex structures like tissue patterns and intensity differences. The deeper layers identify high-level semantic features, such as tumor shape,

irregular growth patterns, and abnormal tissue regions. This progressive feature learning makes VGG-16 highly effective for distinguishing between normal and malignant lung **tissues.**

Fig-3:Summaryofthemodel

3.4 Objectives

The objectives of the research paper on lung cancer detection using the VGG-16 architecture are multifaceted. Firstly, it aims to address the urgent need for early detection of lung cancer, a pressing healthcare challenge associated with high mortality rates. Leveraging deep learning techniques, particularly the VGG-16 algorithm,the project seeks to develop an accurate and user-friendly system for detecting lung cancer from MRI scan images.

By focusing on improving model interpretability, enhancing image quality, and handling class imbalances through various techniques like noise cancellation, contrastenhancement,andoversampling,theprojectaims to achieve unbiased and reliable predictions. The ultimate goal is to create a VGG-16 system capable of accurately detecting benign and malignant lung lesions, thereby improving patient prognosis and treatment outcomes. Additionally, the project aims to develop user-friendlyweb applications with robust security measures for data encryption and user authentication, ensuring compliance with healthcare regulations while optimizing scalability and task efficiency.

Overall, the objectives encompass advancing lung cancer detectionthroughinnovativedeeplearningmethodologies

and practical deployment strategies to benefit both patients and healthcare professionals alike.
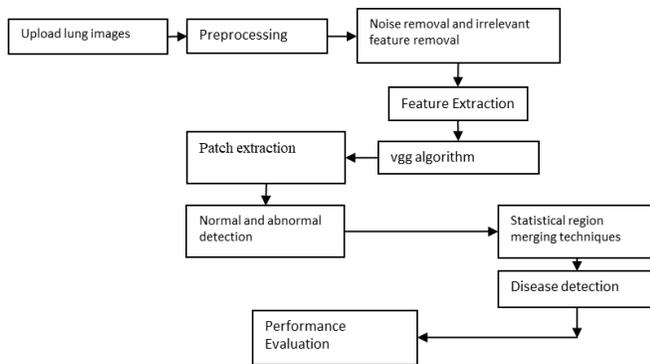
IV. SYSTEMMETHODOLOGY

4.1 Flowchart

Fig-4:Aflowchartrepresentingthemethodology

4.2 Dataset Creation

The dataset he dataset creation process is a crucial step in developing an accurate and reliable system for Lung Tumor Segmentation Using Visual Geometry Group Networks in MRI Images. A well-structured dataset ensures that the VGG-based CNN model can effectively learn the distinguishing features between normal and malignant lung tissues.

Initially, lung MRI images are collected from reliable medical imaging sources such as hospitals, diagnostic centers, or publicly available medical databases. The dataset includes MRI scans of both healthy individuals and patients diagnosed with lung tumors. Each image is carefully labeled by medical experts to ensure correct classification into categories such as Normal and Malignant. Accurate labeling is essential for supervised deep learning training.

The collected MRI images are organized into structured folders based on class labels. For example, separate directories are created for normal and tumor cases to facilitate efficient data loading during training. To improve the diversity and robustness of the dataset, images are collected from different age groups, genders, and tumor stages. This helps the model generalize better to real-world clinical scenarios.

After collection and labeling, the dataset undergoes preprocessing steps such as resizing, normalization, noise removal, and segmentation. Data augmentation techniques like rotation, flipping, zooming, and brightness adjustment are applied to artificially increase the dataset size and prevent

overfitting. This is especially important when the number of available MRI images is limited.

Finally, the complete dataset is divided into three subsets: training, validation, and testing. Typically, 70% of the images are used for training, 15% for validation, and 15% for testing. The training set is used to learn model parameters, the validation set helps in tuning hyperparameters, and the test set evaluates the final performance of the model.
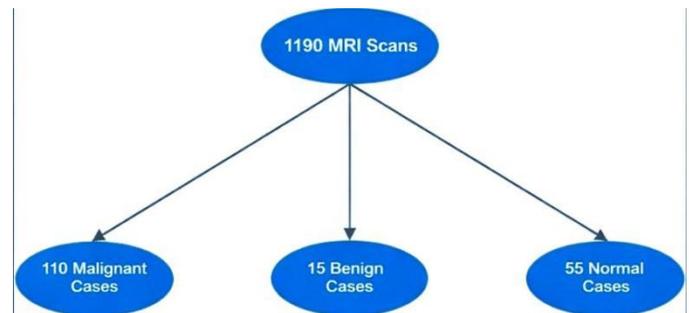

Fig-5:OverviewofDataset

4.3 Model Training

The dataset is split into training, testing and validation sets.. This distribution is crucial for training a robustmodel that can accurately identify cancer as Malignant, Benign or Normal from lung images. The initialdistribution combines the test and validation sets,ensuring an appropriate distribution of samples into different sets. This layered approach helps preserve the representation of both malignant and benign cases in each subset.Duringrotation,the VGG-16architectureis used as a powerful feature collector that exploits its ability to capture complex patterns and features of medical images. The model is initialized with weights pre-trained on large-scale image datasets such as ImageNet, allowing it to learn meaningful representations for lung cancer detection.Fine-tuning the VGG-16 model involves updating its parameters using back propagation and optimization techniques. such as stochastic gradient descent (SGD) or Adam. This process facilitates the adaptation of pre-trained features to the specific characteristics of lung cancer image data. In addition, data augmentation strategies such as rotation, scaling, and translation are applied to the training images to increase the diversity of the dataset and improve the model's ability to generalizeto unseen data. During training, hyperparameters such as learning. rate, set size and regularization strength are carefullyadjustedtooptimizethemodelperformance.

The trainingloss isiterativelymonitoredandminimized, while the validation set is used to assess the generalizability of the model and avoid overfitting. Performance metrics

including accuracy, sensitivity, specificity, and the area under the receiver operating curve (AUC-ROC) are calculated during training to evaluate the performance of the model in lung cancer lesions. upon detection. This thorough evaluation ensures that the trained model can malignant and benign cases.

4.4 Model Testing

The real-world applicability of the model and its ability to help clinicians accurately diagnose lung cancer based on medical imaging data. The model testing step is necessary to evaluate the performance of the lung cancer detection modelgeneratedbytheVGG-16algorithm.Afterthemodel is trained, accuracy and loss metrics are visualized over successive time periods to monitor the learning dynamics of the model and identify potential over- or under-fitting problems. Evaluation metrics such as accuracy and lossare then calculated for both the training and validationsets to measure the generalization ability of the model. Evaluation results, including training, validation, and accuracy on independent test sets, as well as relevant training parameters such as image dimensions, learning rate, and set size, are compiled to provide acomprehensive overview of model performance. In addition, all the time spent in the training and evaluation processes is recorded to evaluate the effectiveness of the calculation. In addition, a confusion matrix is createdbased on the test predictions ofthe model, which provides insight into the distribution of true positive, true negative, false positive and false negative predictions in different categories of lung images. This analysis helps identify potential errors or deviations in model predictions and provides valuable feedback for model refinement and improvement. Overall, the model testing phase ensuresthe readiness of the VGG-16-based lung cancer detection model for use in clinical settings, which will help improve diagnostic accuracy and patient care.

4.5 Output and Representations

The final accuracy and performance metrics of the model are substantiated visually through a series of graphs and charts, showcasing accuracy and loss metrics across epochs forboth training and testing datasets. Additionally, confusion matrices are created to represent classification performanceonbothtrainingandtestingdata,providinga clear and concise understanding of the model's behavior. Complementing these metrics are tumor imagesdisplaying predicted classes alongside model confidence scores, offering valuable insights into the model's effectiveness and emotional impact. This comprehensive presentation notonly evaluates efficacy but also facilitates

furtherrefinementandoptimization,ultimatelyenhancing overall performance for end-users.

V. OVER VIEW OF TECHNOLOGIES

In our pursuit of lung cancer detection using MRI scans, the VGG16algorithmstandsasapivotalcomponentwithinthe broader landscape of machine learning and computer vision. Anchored upon the TensorFlow framework, our research harnesses the power of VGG16, a preeminent convolutional neural network architecture renowned for its effectiveness in image classification tasks. TensorFlow, servingasthebedrockofourmethodology,offersaflexibleenviron mentconducivetotheimplementationand fine-tuning of deep learning models such as VGG16. This synergy enables the seamless integration of advanced neural network architectures into our workflow, facilitatingtheanalysisofintricatepatternswithinMRIscan images indicative of lung cancer. Furthermore, OpenCV assumes a central role in our research paradigm, facilitating critical preprocessing tasks and enhancing the interpretability of MRI scan data. Through OpenCV, we adeptly extract frames from MRI scan images, enabling the creation of comprehensive datasets essential for training the VGG16 model. Moreover, OpenCV's rich suite of functionalities enables seamless color space conversion and feature manipulation, augmenting the quality and utility of input data for subsequent analysis. In essence,the integration of VGG16 within the TensorFlow framework, complemented by the versatile capabilities of OpenCV, forms the cornerstone of our approach to lung cancer detection. Through this amalgamation of cutting-edge algorithms and tools, our research endeavors culminate in a robust framework capable of discerning subtle abnormalities indicative of lung cancer within MRI scan images, thereby contributing to advancements in early diagnosis and treatment of this devastating disease.

VI. RESULTS AND DISCUSSIONS

The VGG- 16 model's performance on the IQ- OTH/ NCCD lung cancer dataset isexhaustively presented through a collection of visual aids. These include graphs and charts depicting accuracy and loss metrics over epochs for both training and testing datasets. Likewise, confusionmatrices are generated to illustrate the classification performanceof the model on both training and testing data. This detailed representation offerspreciousperceptivity into the behavior and efficacy of the VGG- 16 model on the specified dataset.
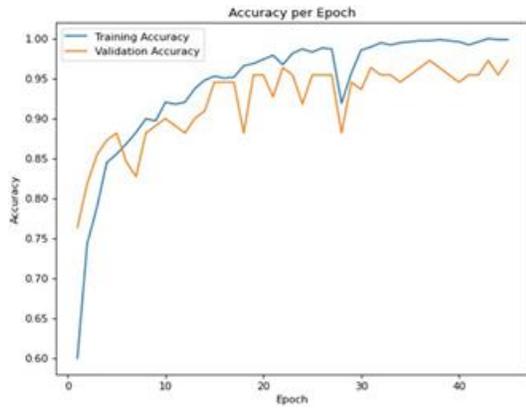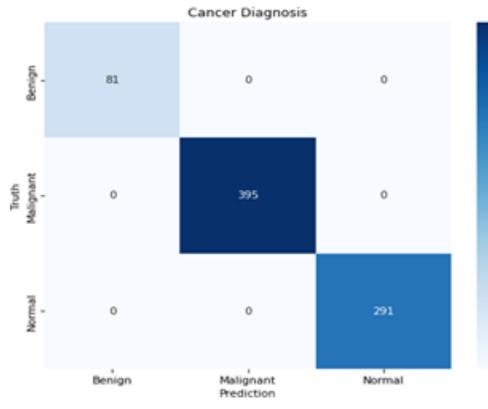
Fig-6:Training&Validation AccuracyperEpoch

Fig-7:Training&ValidationLossperEpoch
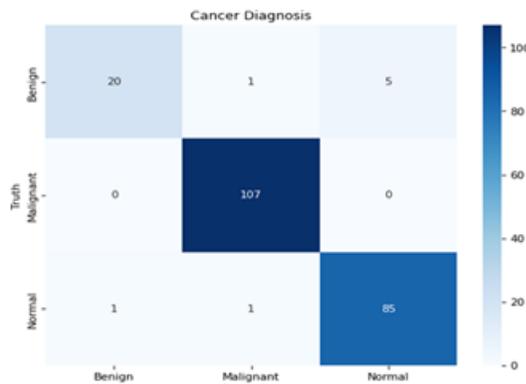
Fig-8:ConfusionMatrixforTestdata

Fig-9:ConfusionMatrixforTraindata

Table-I:AccuracyandLossComparisonofModel

Index	Model	Train Acc.	Train loss	Val. Acc.	Val. loss
1.	VGG-16	99.87%	0.0134	97.27%	0.1346

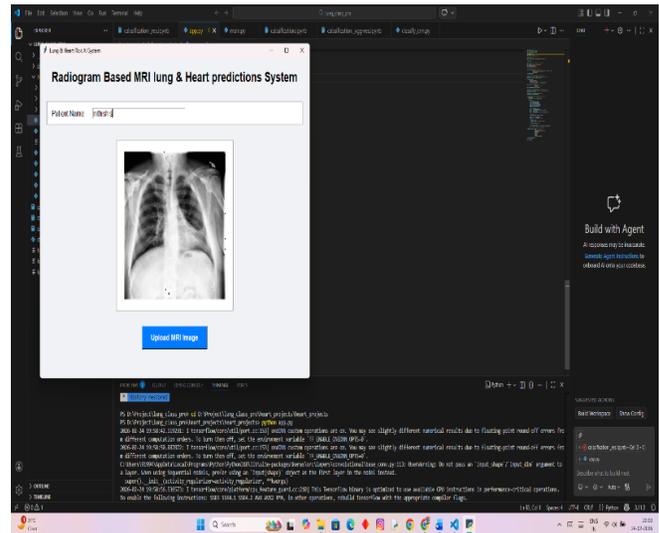**Output:**
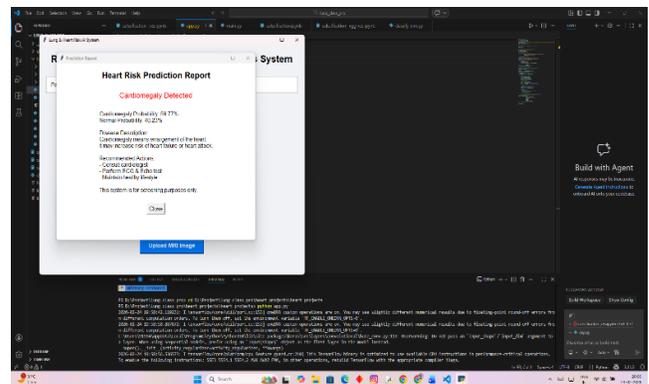

Fig-10:PredictionResultforuploadedimage

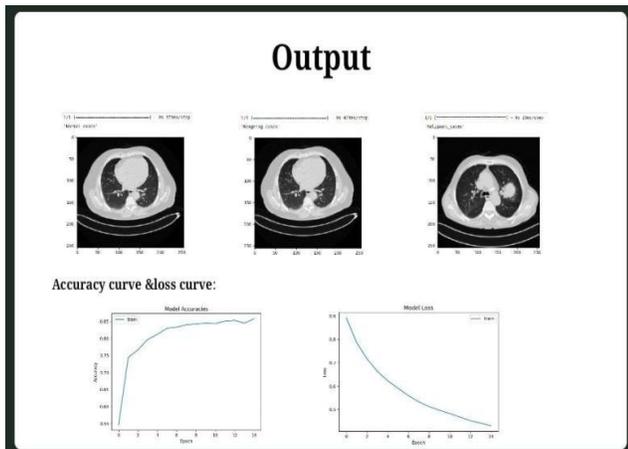**Fig–11:PredictionResultforuploadedimage**

Fig–12:PredictionResultforuploadedimage

VII. CONCLUSION & FUTURE SCOPE

In conclusion, the utilization of VGG16 algorithm for lung cancer detection based on MRI scan images offers a promising avenue for early diagnosis and intervention. Through this research, it has been demonstrated that the deep learning model can effectively analyze intricate patterns within MRI scans, distinguishing between malignant and benign nodules with high accuracy and efficiency. The integration of VGG16 into medical imaging holds tremendous potential for enhancing the diagnostic process, enabling clinicians to make more informed decisions and improve patient outcomes.

Furthermore, the findings of this study underscore the importance of leveraging cutting-edge technologies in the realm of healthcare. By harnessing the power of artificial intelligence and machine learning.

we can augment the capabilitiesofmedicalprofessionals,streamlinediagnostic procedures, and ultimately, save lives. However, it'scrucial to acknowledge that the development and implementation of such algorithms necessitate rigorous validation, continuous refinement, and adherence to ethical guidelines to ensure their reliability and safety in clinical practice.Looking ahead, further research and collaboration are needed to enhance the robustness and generalizability of VGG16-basedlungcancerdetectionsystems.This includes exploring larger and more diverse datasets, refining the algorithm's architecture, and investigating potential integrationwithothermodalitiesforcomprehensive.patient assessment. Ultimately, by advancing the field of computer-aided diagnosis in oncology, we can strive towards earlier detection, personalized treatment strategies, and improved prognosis for individualsaffected by lung cancer. The future scope would include.

Enhanced Diagnostic Precision:

- Continued refinement and validation of theVGG16 algorithm are expected to result in heightened sensitivity and specificity in detecting lung cancer nodules on MRI scans.
- This advancement could significantly improve diagnostic precision, leading to earlier detectionof the disease and subsequent treatmentinitiation.

Facilitation of Personalized Medicine:

- The deep learning capabilities of the VGG16 algorithm enable precise characterization of lung cancer subtypes and tumor characteristics.
- This could pave the way for personalized treatment approaches tailored to individual patients, resulting in improved therapeutic outcomes and reduced adverse effects.

Integration in to Clinical Practice:

- Integration of the VGG16 algorithm into clinical workflows has the potential to streamline diagnostic processes for healthcare professionals.
- By automating nodule detection and characterization tasks, clinicians can allocatemore time to patient interaction and treatment planning, ultimately enhancing the quality of care provided.

Expansion of Screening Programs:

- ThesuccessfulapplicationoftheVGG16algorithm in lung cancer detection could support the expansion of population-based screening programs.
- With improved accuracy in identifying high-risk individuals,screeningeffortscouldbeoptimized to target those most likely to benefit from early detection, potentially reducing disease-related mortality rates.

Catalyst for Technological Advancements:

- ThedevelopmentandvalidationoftheVGG16 algorithm represent a milestone in the intersectionofartificialintelligenceandmedical imaging.
- This success is likely to inspire further research and innovation in the field, driving the development of even more sophisticated algorithms capable of detecting various diseases from imaging data.

Ethical Considerations and Challenges:

- As the use of artificial intelligence in healthcare continues to expand, it is essential to address ethical considerations such as data privacy, algorithm bias, and transparency.
- Additionally, challenges related to algorithm interpretability, regulatory compliance, and clinician adoption may need to be navigated to ensure the successful integration of the VGG16 algorithm into clinical practice.

Future Directions:

- Future research directions may include the exploration of multi-modal imaging approaches, such as combining MRI with other imaging modalities or genomic data, to further enhance diagnostic accuracy and predictive capabilities.
- Longitudinal studies assessing the impact of VGG16-based lung cancer detection on patient outcomes and healthcare economics couldprovide valuable insights into its clinical utility and cost-effectiveness.

REFERENCES

[1] Shariff, V., Paritala, C., & Ankala, K. M. (2025). Optimizing non small cell lung cancer detection with convolutional neural networks and differential augmentation. Scientific Reports, *15*(1), 15640.

[2] Ozdemir, B., Aslan, E., & Pacal, I. (2025). Attention enhanced inception next based hybrid deep learning model for lung cancer detection.

[3] UrRehman, Zia, et al. Effective lung nodule detection using deep CNN with dual attention mechanisms. Scientific Reports 14.1 (2024): 3934.

[4] Gautam, N., Basu, A., & Sarkar, R. (2024). Lung cancer detection from thoracic CT scans using an ensemble of deep learning models. Neural Computing and Applications, 36(5), 2459-2477.

[5] Shahadat, Nazmul, Ritika Lama, and Anna Nguyen. Lung and colon cancer detection using a deep ai model. Cancers 16.22 (2024): 3879.

[6] Prasad, Umesh, Soumitro Chakravarty, and Gyaneshwar Mahto. "Lung cancer detection and classification using deep neural network based on hybrid metaheuristic algorithm: U. Prsad et al." *Soft Computing* 28, no. 15 (2024): 8579-8602.

[7] Singh, Onkar, Kanchan Lata Kashyap, and Koushlendra Kumar Singh. "Lung and colon cancer classification of histopathology images using convolutional neural network." *SN Computer Science* 5.2 (2024): 223.

[8] Sheela, M. S., Amirthayogam, G., Hephzipah, J. J., Gopalakrishnan, S., & Chand, S. R. (2024). Machine learning based lung disease prediction using convolutional neural network algorithm. *Mesopotamian Journal of Artificial Intelligence in Healthcare*, *2024*, 50-58.

[9] Mohandass, G. H. K. D. S. C. S. G., et al. "Lung cancer classification using optimized attention-based convolutional neural network with DenseNet-201 transfer learning model on CT image." *Biomedical Signal Processing and Control* 95 (2024): 106330.

[10] Sangeetha, S. K. B., Sandeep Kumar Mathivanan, P. Karthikeyan, Hariharan Rajadurai, Basu Dev Shivahare, Saurav Mallik, and Hong Qin. "An enhanced multimodal fusion deep learning neural network for lung cancer classification." *Systems and Soft Computing* 6 (2024): 200068.

[11] Sivasankaran, Prasath, and Karthiga Rani Dhanaraj. "Lung Cancer Detection Using Image Processing Technique Through Deep Learning Algorithm." *Revue d'Intelligence Artificielle* 38.1 (2024).

[12] Hussain Ali, Y., Sabu Chooralil, V., Balasubramanian, K., Manyam, R. R., Kidambi Raju, S., T. Sadiq, A., & Farhan, A. K. (2023). Optimization system based on convolutional neural network and internet of medical things for early diagnosis of lung cancer. *Bioengineering*, *10*(3), 320.

[13] Musthafa, M. Mohamed, et al. "Optimizing double-layered convolutional neural networks for efficient lung cancer classification through hyperparameter optimization and advanced image pre-processing techniques." *BMC Medical Informatics and Decision Making* 24.1 (2024): 142.

[14] CHAKRABORTY, SANJUKTA, and D. D. K. Banerjee. "A study on the hybrid approach for lung cancer detection using convolutional neural networks and decision trees." *vol* 10 (2024): 786-801.

[15] Thanammal, K. K. "Lung cancer detection via deep learning-based pyramid network with honey badger algorithm." *Measurement: Sensors* 31 (2024): 100993.