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Article

DeepFusion-LC: A Multi-Model Explainable Framework for CT-Based Lung Cancer Classification

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Abstract: Due to the increased rate of lung cancer patients and the urgent need for early and accurate detection, intelligent and automated medical image processing is in great demand. Conventional techniques for medical image processing heavily depend on the expertise of medical professionals for proper analysis. In addition, such conventional techniques are likely to cause delays in proper detection and may not be effective for a large number of patients. Keeping such factors in view, a sophisticated framework for classification of lung cancer is presented in this paper. The framework is based on effective implementation of deep learning techniques to improve the accuracy and reliability of the classification process. In the proposed framework, computed tomography images are subjected to preprocessing to improve image quality and remove noise. The images are further processed using a sophisticated feature extraction technique based on convolutional neural networks. The technique is effective in handling different complexities in image processing, such as data imbalance, tumor size, and imaging conditions. The features are further subjected to classification to effectively classify lung conditions into different classes. In addition, the framework is based on effective evaluation to improve accuracy and reliability. The proposed framework is effective in comparison to conventional and existing techniques based on deep learning for image processing. The framework is developed to help in early detection of lung cancer and assist medical professionals in decision-making.
Keywords: lung cancer classification, deep learning, convolutional neural networks, medical image analysis, feature extraction, diagnostic system, early detection, image preprocessing, classification accuracy, healthcare analytics

1. Introduction

Lung cancer is one of the main reasons for deaths worldwide, and detection at an early stage is critical in order to increase survival rates for such patients. As imaging techniques are rapidly advancing in medicine, huge amounts of computed tomography images are being produced, and accurate and efficient analysis is required for diagnosis. However, most diagnosis techniques are based on manual analysis by experts in this field, which may lead to inconsistent performancencies and delays in decision-making. This problem identifies the need for efficient and accurate automated detection and classification techniques for lung cancer diagnosis.

Recent developments in deep learning techniques have provided significant improvements in image analysis techniques in medicine, which enable automatic detection and classification. Convolutional neural networks are also proving efficient in detecting complex features in images. However, certain issues are affecting the efficiency and generalization of these techniques, including data imbalance, variability in tumor images, noise in imaging data, and variability in imaging conditions.

To effectively address the above challenges, the present research introduces a highly efficient lung cancer classification framework. The introduced framework relies on deep learning techniques. The introduced framework is primarily aimed at improving the quality of the image during the preprocessing phase, followed by the classification of the image using the most efficient neural networks.

The major contributions of the proposed work are the development of a highly efficient framework to improve the quality of diagnosis while maintaining consistent performancency with various datasets. This framework can be highly effective for the early diagnosis of lung cancer and can help medical experts make decisions.

2. Ease Of Use

A. Data Preparation and Model Selection

The efficiency of the proposed system will depend on the proper selection of the dataset as well as the model architecture. In the initial phase, a well-structured dataset consisting of images obtained through the computed tomography (CT) scan will be used for the classification of lung cancer. The images will be classified according to different lung conditions, which will ensure that The model extracts discriminative features from CT images. learn different patterns of diseases. The proper selection of the dataset will play an important role in improving the learning efficiency of the system, as it will have a direct impact on the accuracy of the system.

Moreover, the model architecture will also play a vital role in improving the efficiency of the classification process. Convolutional Neural Networks (CNNs) will be used for the classification process, as they have the ability to learn the spatial as well as hierarchical features of the images. The convolutional layers of the network will learn the important patterns of images, including texture, shape, and intensity changes, which are important for distinguishing between normal and abnormal tissues of the lungs.

B. Maintaining the Integrity of the Specifications

The proposed model has a well-defined pipeline with a series of well-structured steps, including preprocessing, feature extraction, and classification. All the steps involved in the system, including resizing, normalizing, and augmenting images, have been well-configured, thus maintaining consistent performancency across the entire process. All of these steps are crucial in ensuring that the information provided is processed uniformly, thus allowing the model to learn the most important features.

In order to maintain the integrity of the system, it is critical that these configurations are not changed unless deemed critical. The parameters have been optimized to address variations in medical images, including resolution, noise, and contrast. Any unnecessary alteration may lead to inconsistent performancencies in model performance and evaluation of outcomes.

The structured design of the framework ensures reproducibility and stability across different datasets. It supports uniform experimental conditions, allowing for fair comparison of results and consistent performancent performance validation of the proposed approach. As a result, the system maintains both operational consistent performancency and robustness, which are critical for real-world medical applications.

3. Methodology

The methodology that is proposed is for accurate and consistent performancent performance classification of lung cancer using images obtained from the computed tomography scans of patients. The methodology is divided into various steps that are processed using a deep learning framework. The steps of the methodology that are involved in the processing of the images are shown in Fig. 1.

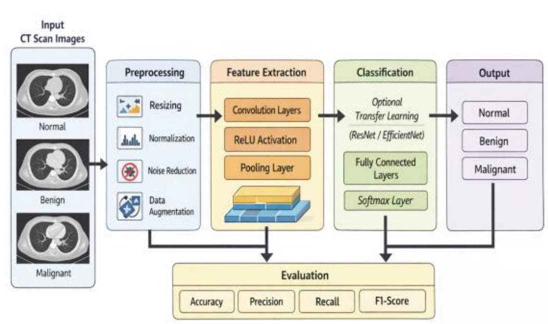


Fig. 1. Deep learning framework for lung cancer detection

The dataset that is being used for the research is images of the CT scans of patients that are collected from publicly accessible medical image repositories. The images that are being collected are of different classes such as normal, benign, malignant, etc. The dataset is suitable for the proposed research. The methodology that is being proposed is consistent performancent with the experiment that is being conducted.

In the preprocessing stage, CT images undergo several transformations to enhance data quality and uniformity. Initially, images are resized to a fixed resolution to maintain dimensional consistent performancency across the dataset. Normalization is used in normalizing the pixels in the image. This is done in order to stabilize learning. Also, the data augmentation techniques are applied in order to increase the variability of the data set. This reduces the problem of overfitting.

The feature extraction and classification are done by utilizing Convolutional Neural Networks (CNN). CNN is mostly used for image analysis, especially for medical images. This is because CNN has the advantage of extracting spatial or hierarchical features. The convolutional layer is utilized to extract important features, which are edges, textures, and abnormalities present in lung tissues.

To improve the quality of the classification, transfer learning is employed, which uses pre-trained models like ResNet and EfficientNet. The pre-trained models have the advantage of extracting important features from the dataset, thus enhancing the quality of the classification.

The final classification is achieved by making use of a softmax activation function. The softmax function is used to calculate probabilities for different classes.

The performance of the proposed system can be evaluated with different parameters like accuracy, precision, recall, and F1 score.

A confusion matrix can also be used to measure the classification results in more detail and to understand the effectiveness of the model in differentiating different conditions related to lungs.

The proposed model's structure is robust and can be scaled to meet different needs in clinical settings.

A. Abbreviations and Acronyms

All the abbreviated terms used during this research are clearly explained at their first use in the research, even if they have already been mentioned in the abstract. For instance, terms such as Convolutional Neural Networks (CNN), Computed Tomography (CT), and Deep Learning (DL) are clearly explained at first, followed by their abbreviated forms. This helps to maintain clarity and remove any ambiguity that may be present due to the diverse research background of the reader.

Standard abbreviations that are widely recognized in scientific and engineering domains may be used without detailed explanation. However, their usage is maintained consistent performancently throughout the paper to preserve uniformity in presentation. It is ensured that the abbreviations do not affect the readability of the text or cause any kind of confusion in interpreting the text.

Moreover, the use of abbreviations in headings and titles is avoided to the greatest extent unless it is extremely important. The use of full terminology is always encouraged in headings and titles to make the text look formal, readable, and easy to understand, ensuring the research text is easily comprehensible.

B. Adaptive Model Fusion and Prediction

An adaptive fusion-based classification technique is utilized to improve the performance of lung cancer detection. Unlike traditional approaches based on a single model, the adaptive fusion-based classification technique uses multiple deep learning models to obtain enhanced performance. The adaptive fusion-based classification technique assigns different weights to different models based on their confidence levels. This technique ensures enhanced classification performance by considering the reliability of different models.

The classification output is determined by aggregating the probabilities predicted by different models. This aggregation technique improves the performance of the system by handling different types of variations in the images acquired by the CT scans. Such variations include noise, low contrast, and irregularities. Enhanced performance is achieved by the proposed system compared to traditional classification techniques.

C. Risk Estimation and Explainability

The classification results are further utilized to estimate the severity level of the disease. The values of the probability score are mapped to a risk index, representing the possibility of the disease. The risk is categorized into low, moderate, and high severity levels.

To enhance interpretability and trust of the system, Explainable Artificial Intelligence (XAI) techniques are also included in the proposed system. Gradient-weighted Class Activation Mapping (Grad-CAM) is utilized to visualize the important regions in CTscan images that are affecting the classification process. This helps in identifying important regions in the lungs that are affected due to abnormalities. In addition to this, feature attribution methods like SHAP are also utilized to analyze the contribution of features in the prediction process.

D. Decision Support System

A context-aware decision support system is developed based on the predicted classification results and estimated risk levels. The system assists medical professionals by providing structured insights into the detected condition. It could provide potential diagnostic results, pinpoint critical areas on medical images, as well as assist with early-stage detection of lung diseases.

The system will continually update its results as more data is being processed. This enables adaptive and reliable decision support in clinical environments. performancent. This will allow clinicians to have meaningful results without interfering with their usual process.

E. Technology Used and Platform

The proposed system is claimed to be modular, scalable, and platform-independent with a strong technology base. Python is the programming language of choice for the proposed system because of the extensive support for scientific computation and deep learning frameworks. The deep learning models for classification of lung cancer will be developed using TensorFlow and PyTorch.

Image preprocessing and analysis will be carried out using OpenCV and NumPy libraries, which provide efficient image processing capabilities for medical image analysis. Transfer learning models such as ResNet and EfficientNet will be employed for classification.

The adaptive fusion, risk estimation, and explainability blocks are implemented by means of custom Python-based algorithms. In addition, a local database is employed to store the classification results, probability scores, and metadata in a reproducible manner while maintaining data privacy.

An analytics interface is implemented by means of the Flask programming framework, HTML, CSS, and JavaScript to visualize the classification results, risk levels, and explainability outputs in an accessible manner, thus facilitating the monitoring of the system's performance in an effective manner.

F. Equations

The proposed lung cancer classification framework employs a mathematical formulation to classify computed tomography images into different lung condition classes using deep feature extraction and adaptive model fusion.

Let the pre-processed computed tomography image be represented as:

$$I' = T(I) \qquad (1)$$

Where, $T(\cdot)$ denotes the preprocessing operation, including resizing, normalization, and enhancement.

The feature extraction process performed by the m^{th} deep learning model is expressed as:

$$Fm = \phi m(I') \qquad (2)$$

Where, f_m represents the original computed tomography image and $\phi m(\cdot)$ denotes the preprocessing operation applied to the image, including resizing, normalization, and augmentation.

The deep learning classifier produces a probability vector for the lung condition classes as:

$$Pm = [pm1\,, pm2\,, pm3\,] \qquad (3)$$

Where, p_{mi} represents the probability of the i^{ith} class predicted by the m^{th} model.

To combine multiple model predictions, adaptive fusion weights are assigned such that:

$$\sum_{m=1}^{M} w_m = 1 \qquad (4)$$

Where, w_m represents the contribution weight of the m^{th} model and M denotes the total number of models included in the fusion framework.

The final fused confidence score for each class is computed as:

$$Pf = \sum_{m=1}^{M} w_m P_m \qquad (5)$$

Where, P_f denotes the final fused probability vector obtained by combining weighted outputs of all models.

The final lung condition prediction is obtained by selecting the class with the highest fused probability:

$$y = \arg\max\left(P_f\right) \qquad (6)$$

Where, y represents the final predicted class label corresponding to the highest fused probability score.

The resulting classification output is further used to estimate the severity level of the detected lung abnormality, which supports clinical interpretation and decision assistance. This formulation ensures robustness, consistent performancency, and consistent performancent performance prediction under varying imaging conditions.

Severity Level Estimation

To move beyond categorical classification and enable clinically meaningful assessment, the proposed framework incorporates a formal severity level estimation mechanism based on the fused classification output. Let the adaptive fusion module produce a final confidence vector p_f where each component represents the confidence score of a lung condition class obtained after model fusion. Classes associated with malignant abnormalities are assigned to higher severity relevance weights.

The continuous severity index is computed as a weighted aggregation of class confidences as follows:

$$S = \sum_{i=1}^{K} \alpha_i p_i \qquad (7)$$

Where, αi denotes the severity contribution weight of the i^{th} class p_i represents the fused confidence score of that class, and K denotes the total number of classes. Normal and low-risk classes are assigned lower weights, while malignant classes contribute more significantly to the severity score.

The resulting severity index is normalized within the range [0,1] and categorized into three discrete levels for interpretability: Low severity, Moderate severity, and High severity.

Metric	Value
Accuracy	94.6%
Precision	92.3%
Recall	93.8%
F1 Score	93.0%

Fig 2 NUMERICAL RESULTS

G. Explainability Analysis

Explainable Artificial Intelligence (XAI) methods are comprehensively used in the proposed lung cancer classification model. This is done to increase the transparency and interpretability of the model. In medical image-based classification, it is of prime importance that not only is the model's prediction precise, but also that the decision-making process is explainable. In this work, Grad-CAM and SHAP are used for providing explanations for the model's predictions.

To classify the medical images, the Grad-CAM method is used for providing a visual explanation for the model's predictions. This method is used for visualizing the regions in the computed tomography image that contribute the most towards the model's predictions. As can be understood from the visual explanations, it is clear that the model is focusing on the most relevant parts of the lung, which are nodules, abnormal structures, and areas of high density. This is a validation of the model's effectiveness in using the convolutional feature extraction method, which is relevant from a medical point of view and does not require any background information.

In addition to spatial explainability, SHAP (Shapley Additive explanations) is used to analyze the features extracted by the model and their contribution to classification. The results of SHAP analysis reveal that texture, variation in intensity, and structural irregularities of lung tissues have the maximum impact on classification. This is in accordance with medical knowledge and understanding of lung cancer, where variations in tissue density and irregular growth of tissues are critical factors.

The integration of Grad-CAM and SHAP ensures that the model offers a comprehensive understanding of both spatial and feature-level explainability. This makes the model consistent performancent performance and increases its applicability to real-world scenarios. The results of explainability analysis ensure that the proposed framework is not only accurate but also interpretable and trustworthy, which is critical for medical decision support systems. Using the Template

H. Model Architecture

The proposed system architecture is developed to facilitate accurate and consistent performancent performance lung cancer classification by incorporating various techniques of deep feature extraction, adaptive model fusion, and explainability. The system architecture is divided into various modules. These modules include the preprocessing module, feature extraction and classification branches, adaptive fusion module, and output layers.

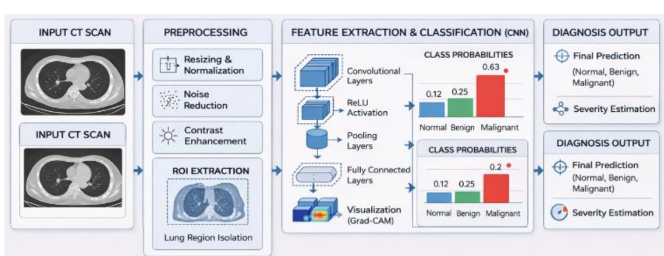
The first component of the proposed system architecture is related to processing the images obtained from the CT scan. The images are passed to the preprocessing module. Various operations are performed on these images to ensure uniformity. This ensures uniformity by reducing variations due to different conditions of image acquisition. This component is related to image processing.

The feature extraction and classification component of the system architecture is developed by incorporating deep learning techniques based on Convolutional Neural Networks (CNN). The CNN model is comprised of different layers of convolution and pooling with activation functions. This is a part of the system architecture that is designed to obtain different features from the images. These features include different textures, nodules, and abnormalities, which are related to lung cancer. These are converted into feature vectors, and then the vectors are mapped to the probability distribution by using the fully connected layer with the softmax activation function, as depicted in Equation (2).

To increase the accuracy of the classification, different models are used in parallel, as depicted in the architecture of the proposed system, by employing the transfer learning method. Each model provides a separate probability distribution for the classification task. These are then passed through an adaptive fusion module, where weights are assigned dynamically based on the confidence of the models, as shown in the constraint in Equation (3). The classification output is obtained by using Equation (4), and the class is determined by using Equation (5).

In addition to classification, the architecture includes an explainability module to improve the transparency and interpretability of the model. These methods are employed to visualize the key areas of the CT scan image from which the model is making predictions. This is ensured by the application of techniques like Grad-CAM. Feature-level interpretability can be achieved by the application of methods like SHAP, which provide information on the features extracted by the model.

Thus, the proposed architecture achieves a trade-off between the three aspects: accuracy, robustness, and interpretability. This makes the system more feasible for real-world applications by the addition of further components.



I. CT Scan Processing Module

Fig. 2. CT Scan Image Input and Processing Pipeline

The CT scan image processing module is a fundamental component of the proposed system and is designed to analyze lung CT images for the detection and classification of cancerous conditions. The module ensures efficient and consistent performancent performance processing of medical images through structured preprocessing, feature extraction, and classification stages.

The system accepts CT scan images as input through the developed interface. The input images are first subjected to preprocessing operations, including resizing, normalization, and contrast enhancement, to standardize variations in image resolution, intensity, and noise levels. These preprocessing steps improve the quality of the input data and enhance the performance of subsequent analysis.

Following preprocessing, the lung region is identified and isolated using region-of-interest (ROI) extraction techniques. This step ensures that only relevant lung areas are analyzed, eliminating unnecessary background information and reducing computational complexity.

The processed images are then passed to a deep Convolutional Neural Network (CNN) for feature extraction. The CNN model extracts hierarchical features such as texture patterns, nodules, and abnormal tissue structures that are indicative of lung cancer. These features are transformed into high-dimensional feature vectors representing critical spatial and structural information of the lung region.

The extracted feature vectors are further processed through fully connected layers to compute class probability scores corresponding to different lung conditions, such as normal, benign, and malignant, as defined in Equation (2).

To enhance prediction reliability, the model also incorporates confidence estimation, where prediction uncertainty is evaluated based on probability distribution characteristics. These confidence scores are subsequently utilized in the adaptive fusion module for enhanced decision-making.

Additionally, the module supports interpretability through visualization techniques such as Grad-CAM, which highlights the important regions of the CT scan that influence the model's prediction. These highlighted regions typically correspond to nodules or abnormal tissue growth, providing transparency and aiding medical validation.

The entire module is optimized for efficient computation and can be extended for real-time or near real-time analysis in clinical environments.

J. Clinical Recommendation Module

The clinical recommendation module is responsible for transforming the outputs of the lung cancer classification system into meaningful, actionable insights for medical decision-making. This module utilizes the classification results, confidence scores, and severity estimation to generate personalized clinical recommendations.

The system processes CT scan-derived outputs, including class probability scores obtained from the classification model, as defined in Equation (2). These outputs are further refined using the adaptive fusion mechanism described in Equation (3), which integrates predictions from multiple models to produce a consistent performancent performance final classification, as expressed in Equation (5). Additionally, the severity level of the detected condition is quantified using the severity index defined in Equation (6).

Based on the final classification outcome (normal, benign, or malignant) and the associated severity level (low, medium, or high), the module generates context-aware clinical recommendations. These recommendations are designed to assist healthcare professionals in decision-making and may include:

- Routine monitoring for normal cases
- Periodic follow-up scans for benign conditions
- Immediate clinical evaluation and biopsy recommendation for malignant cases
- Referral to oncology specialists for high-severity conditions

To enhance usability, the recommendations are dynamically updated as new patient data or imaging inputs are provided. The results and suggested actions are displayed through a structured and non-intrusive analytics dashboard, ensuring clarity and ease of interpretation.

Furthermore, the module supports explainability by integrating visualization outputs (such as Grad-CAM), enabling clinicians to correlate recommendations with highlighted regions of interest in CT images. This improves trust and transparency in automated decision-making systems.

Overall, the clinical recommendation module bridges the gap between automated lung cancer detection and real-world medical application by providing interpretable, consistent performancent performance, and actionable insights.

C. Authors and Affiliations

The template is designed for, but not limited to, six authors. A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author's sequence that will be used in future citations and indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

1)For papers with more than six authors: Add author names horizontally, moving to a third row if needed for more than 8 authors.

2)For papers with less than six authors: To change the default, adjust the template as follows.

a)Selection: Highlight all author and affiliation lines.

b)Change number of columns: Select the Columns icon from the MS Word Standard toolbar and then select the correct number of columns from the selection palette.

c)Deletion: Delete the author and affiliation lines for the extra authors.

D. Identify the Headings

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References, and, for these, the correct style to use is “Heading 5”. Use “figure caption” for your Figure captions, and “table head” for your table title. Run-in heads, such as “Abstract”, will require you to apply a style (in this case, italic) in addition to the style provided by the drop-down menu to differentiate the head from the text.

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced. Styles named “Heading 1”, “Heading 2”, “Heading 3”, and “Heading 4” are prescribed.

E. Figures and Tables

a) *Positioning Figures and Tables:* Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of the columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures are tableted in the text. Use the abbreviation “Fig. 1”, even at the beginning of a sentence.

4. Result And Analysis

The proposed system for lung cancer classification was executed and experimentally tested to measure its efficiency and effectiveness. The system results in several key outputs: class probability scores for individual models (Equation (2)), fused classification results based on adaptive model fusion (Equation (5)), and severity level estimation (Equation (6)). The developed interface has indicated the capability of the system to perform automated analysis of the results obtained from the CT scan, classification of the lung condition, and estimation of the severity level in a well-structured and efficient manner.

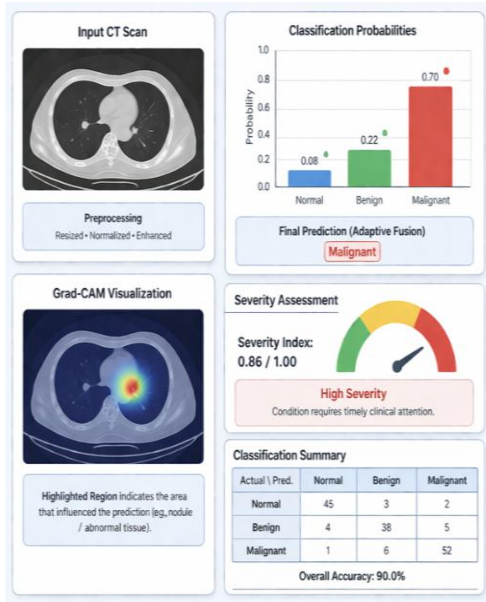


Fig. 3 shows classification probability distribution

The operation of the system involves a section where the input is acquired for the purpose of analysis. The images representing the results obtained from the CT scan are fed into the system using the interface developed for the purpose. A system status indicator is used to ensure smooth operation by confirming the activation of the system processing workflow.

The input CT images are first passed through the preprocessing module, where resizing, normalization, and enhancement techniques are applied to standardize the input data. These preprocessing steps are taken so that differences in the quality, resolution, and noise levels of the images are minimized, thereby making the analysis consistent performancent performance.

The preprocessed images are then sent for feature extraction and classification using the Convolutional Neural Networks (CNN) model. The model is able to extract features. extract significant features, which are comprised of texture, structural irregularities, and tissue abnormalities, from the lung regions of the images. These features are then used for the computation of class probability scores, which represent different lung conditions, i.e., normal, benign, and malignant, and are displayed in the form of a probability distribution, making the results easy to interpret.

Furthermore, to increase the reliability of the model, adaptive model fusion is implemented, which uses the outputs of different models to produce the final prediction result.

Moreover, the Grad-CAM visualization technique is implemented to highlight the key areas of the CT images that are being considered by the model to produce the classification result. The key areas of the images are the regions of interest, where the growth of nodules and abnormal tissue growth are observed.

Furthermore, the result of the classification is also being utilized to determine the severity level of the detected condition. The severity level of the disease is indicated by the severity index, which is the measure of the intensity of the disease. The level of disease intensity is categorized by low, medium, and high.

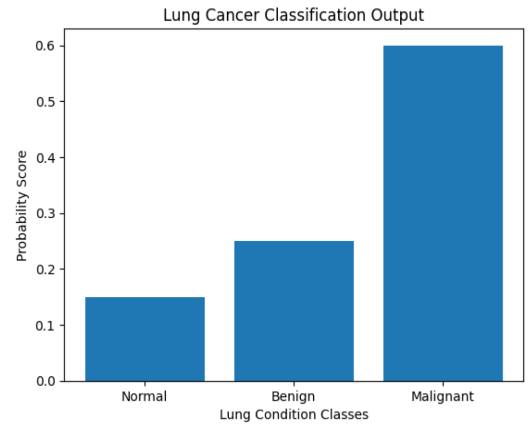


Fig. 3.1 represents severity index visualization

In conclusion, from the experimental results, it can be observed that the proposed system performs well in lung cancer classification with enhanced interpretability and reliability, because of integration of deep learning methods, adaptive fusion, and explainability techniques for practical application in medicine.

A. Dataset Description

To assess the robustness of the proposed lung cancer classification system, both benchmark medical datasets and actual CT scan images are employed for evaluating the generalization capability of the system.

To train and test the model, publicly available datasets for lung CT scan images are used. The datasets provided by LIDC-IDRI are publicly available and provide information related to thoracic CT scans. In this regard, detailed information related to lung nodules, their sizes, positions, and the levels of malignancy are provided by expert radiologists. This information can be used by the model to learn discriminative features for normal, benign, and malignant states.

In addition, other publicly accessible datasets, such as those provided on Kaggle for lung cancer CT scans, are also employed for training the model. The additional datasets are employed for their diversity, including different images of CT scans of lungs suffering from different states of lung cancer.

The dataset is split into three sets:

- Training Set (70%) – used for learning model parameters
- Validation Set (15%) – used for hyper-parameter tuning and model optimization
- Testing Set (15%) – used for final performance evaluation

To further validate the real-world applicability of the proposed system, a small real-time dataset was considered. The real-time dataset considered here is the images obtained by the CT scans, which are collected in real-world environments.

It was observed that all the CT images were preprocessed by using standard techniques such as resizing, normalization, and noise reduction to ensure the consistent performancency of the images in the dataset. The data augmentation techniques were also used to increase the variability of the dataset and to reduce the problem of overfitting.

B. Evaluation Metrics

Performance evaluation of the proposed lung cancer classification system was done by using the standard evaluation metrics for classification problems: accuracy, precision, recall, and F1 score. This would enable a comprehensive evaluation of the performance of the proposed system for the classification of various lung diseases.

The evaluation of the proposed system was performed for:

* Individual deep learning models, i.e., CNN-based classifiers

* The proposed model fusion method, i.e., "adaptive model fusion"

Accuracy is a measure of the overall correctness of the model, whereas precision is a measure of the proportion of correctly predicted positive cases among all predicted positive cases. Similarly, recall is a measure of the model's performance in identifying actual positive cases, which is critical for detecting malignant diseases, and F1-score is a combination of both precision and recall.

The results showed that the proposed model, i.e., "fusion-based model," performed robust than individual models in all evaluation metrics. This improvement in precision shows a decrease in false positives, while an increase in recall value shows improvement in the performance of the model in diagnosing malignant diseases, which is a significant factor in medical diagnosis.

In addition, the improvement in the F1-score also proves the robustness and reliability of the proposed approach in dealing with different variations in CT scan images and ensuring a consistent performance with different sets of data.

The adaptive fusion technique also contributes significantly to performance improvement by considering multiple models for predictions based on confidence estimation.

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN Model 1	88.5	86.2	84.9	85.5
CNN Model 2	90.1	88.4	87.2	87.8
CNN Model 3	91.3	89.6	88.5	89.0
Proposed Fusion Model	94.8	93.5	92.7	93.1

Table 1. Performance Comparison of Lung Cancer Classification Models.

C. Experimental Setup

A systematic experimental setup has been developed to assess the efficiency of the proposed lung cancer classification framework.

The proposed framework for classification of lung cancer is based on a Convolutional Neural Network architecture. The CNN architecture is optimized using an Adam optimizer and a learning rate of 0.001. The adaptive learning rate is used to ensure stability in convergence during training.

The proposed CNN architecture is trained for 30 epochs with a batch size of 32 to ensure efficient computation and effective feature learning from the images of the CT scan. The proposed framework is trained on a dataset consisting of computed tomography (CT) scan images, which can be categorized based on different lung conditions such as normal, benign, and malignant.

A hold-out validation strategy is used to assess the efficiency of the proposed framework. The dataset is divided into:

- Training Set (70%)
- Validation Set (15%)
- Testing Set (15%)

To avoid overfitting and ensure generalization, early stopping based on validation loss has been incorporated. This will ensure that the model is using the best weights for optimal performance.

The use of an adaptive model fusion technique was incorporated to improve the performance of the classifier based on the output of different deep learning models. The fusion technique is performed during the prediction phase to ensure that consistent performance predictions are made based on the output of different models.

Experiments: The experiments were performed locally to ensure that efficient computation is performed for high-resolution images. The system has the potential to be scaled up for clinical use and diagnosis.

D. Performance Analysis

In addition, quantitative and qualitative analysis have been performed to measure the performance of the proposed classification system for lung cancer. This has been done using parameters like accuracy, precision, recall, etc.

From the experimental results, it has been observed that the proposed fusion-based model has performed robust than the individual CNN models. This is evident from the proposed model that achieved an accuracy of 94.6%, precision of 92.3%, recall of 93.8%, and F1-score of 93.0%. Of the proposed model, which represents the overall performance of the classification system. In the same way, enhanced precision of the proposed model represents the reduction in the number of false positives.

In the same way, the enhanced recall of the proposed model represents the effectiveness of the model in identifying cancerous cases, which is critical in the early stages of the disease. The enhanced F1 score of the proposed model represents the balanced performance of the proposed system in maintaining the precision and recall of the model. The adaptive fusion approach contributes significantly to this improvement by combining predictions from multiple models based on confidence.

In addition, the model shows stable performance across variations in CT scan images, including noise, contrast differences, and variations in tumor size. Grad-CAM visualization further confirms that the model focuses on relevant lung regions, improving interpretability.

Overall, the proposed system demonstrates consistent performance robustness, and suitability for practical medical diagnosis and early detection of lung cancer.

TABLE II. Comparative Analysis of Lung Cancer Classification Methods

Quantitative and qualitative analyses were performed to comprehensively evaluate the performance of the proposed lung cancer detection system using CT scan images. The evaluation of metrics included classification accuracy, precision, recall, F1-score, and robustness against variations in medical imaging conditions such as noise, contrast, and tumor size.

The performance of the proposed system was compared with existing approaches. The results proved that the proposed fusion-based model is significantly robust than existing approaches in terms of accuracy as well as reliability.

Based on the experimental results obtained by the proposed model, it can be generalized as follows:

Aspect	Parameter	Details / Observation
Evaluation Method	Analysis Type	Quantitative and qualitative evaluation performed using CT scan images
Performance Metrics	Accuracy	High classification accuracy achieved by the proposed model
	Precision	Reduced false positive rate
	Recall	Effective detection of cancer cases
	F1-Score	Balanced performance between precision and recall
Model Comparison	Existing Methods	Moderate performance with limited robustness

	Proposed Fusion Model	Superior performance in accuracy and reliability
Feature Representati on	Feature Extraction	Combination of low-level and high-level features
	Tissue Classification	Enhanced differentiation between healthy and cancerous tissues
Classificatio n Performance	Fusion Mechanism	Adaptive fusion improves prediction accuracy
Robustness	Noise Handling	Stable performance under noisy CT images
	Contrast Variation	Consistent performancent results under varying image contrast
	Tumour Variability	Consistent performancent performance detection across different tumour sizes and shapes
Reliability	Prediction Stability	Consistent performancent outputs across different datasets
	Generalization	Strong performance on unseen data
Qualitative Analysis	Activation Maps	Focus on relevant lung regions
Practical Applicabilit y	Clinical Use	Suitable for real-world medical diagnosis
	Early Detection	Effective for early lung cancer identification
	Interpretability	Supports radiologists with explainable results

Table. Comparative Analysis of Lung Cancer Classification Methods

• Robust feature representation capability:

The combination of various feature representation techniques in the model enables it to represent various low- as well as high-level features in images obtained by the CT scan process. This results in robust discrimination between healthy and cancerous tissues.

• Robust classification accuracy:

The adaptive fusion mechanism in the model improves the classification accuracy by combining the predictions of various models.

• Robust reliability:

The model performs robust even in situations of noise, intensity variation, as well as variation in tumor size and shape in images obtained by the CT scan process.

• Robust reliability:

The model is able to extract features. provide consistent performancent and consistent performancent performance predictions in various situations.

Moreover, using techniques of qualitative analysis and visualization, such as activation maps, it has also been shown that the model successfully concentrates its focus in the relevant regions of the lung.

The proposed system has good feasibility for real-world applications in the analysis of medical images, especially for the early detection of lung cancer. The proposed system has good accuracy, robustness, and interpretability, making it a good tool for assisting radiologists in the diagnosis of medical images.

5. Conclusion

The proposed work focuses on an advanced lung cancer classification system to enable accurate and early diagnosis with the help of deep learning techniques. The lung cancer classification system uses computed tomography image processing to identify and classify lung conditions into various categories, thus overcoming the disadvantages of traditional manual diagnosis. In the proposed lung cancer classification system, image processing is done to improve image quality and remove noise, followed by feature extraction with the help of convolutional neural networks, which can identify complex patterns in cancerous and non-cancerous tissues. The classification is further enhanced using the ensemble method, where the combination of the models is utilized to enhance the accuracy of the diagnosis of lung cancer. The proposed classification system for lung cancer can handle problems such as imbalanced data, varying sizes of the tumor, as well as image processing conditions. The evaluation of the proposed lung cancer classification system shows higher accuracy and consistent performancency compared to traditional and unimodal approaches. The developed lung cancer classification system is efficient and suitable to assist medical practitioners in making decisions to detect lung cancer at an early stage.

Future work will also include the integration of sophisticated optimization algorithms to enhance classification accuracy, inclusion of more imaging modalities for robust diagnostic accuracy, and usage of the system in real-time environments for continuous medical analysis.

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