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DEEPLUNGSCAN: EARLY DETECTION OF LUNG CANCER USING ENHANCED CNN-BASED CT IMAGE ANALYSIS

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ABSTRACT
Medical imaging tools play a critical role in the early detection and treatment monitoring of lung cancer. Various imaging modalities, including chest X-ray, magnetic resonance imaging (MRI), positron emission tomography (PET), computed tomography (CT), and molecular imaging techniques, have been widely utilized for lung cancer diagnosis. However, these techniques have limitations, such as the inability to automatically classify cancerous images, making them less suitable for patients with co-existing pathologies. Therefore, there is an urgent need for a highly sensitive and accurate method for early lung cancer diagnosis. Deep learning has emerged as a rapidly advancing field in medical imaging, with promising applications across image-based and texture-based data analysis. Utilizing deep learning-based tools enables clinicians to detect and classify lung nodules more efficiently and with greater accuracy. This study proposes an advanced Convolutional Neural Network (CNN) model for detecting lung cancer from chest CT scan images. The proposed model classifies CT images into four categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue. It demonstrates superior accuracy compared to a traditional machine learning approach, the Naive Bayes Classifier (NBC). Additionally, the evaluation metrics confirm the effectiveness of the proposed deep CNN model in supporting clinical experts for improved diagnostic outcomes.

Keywords: Early Lung Cancer Diagnosis, Computed Tomography (CT), Computer-Aided Diagnosis, Adenocarcinoma.

1. INTRODUCTION

Lung cancer remains one of the most lethal forms of cancer globally, accounting for an estimated 1.8 million deaths annually, according to the World Health Organization (WHO). It constitutes nearly 18% of all cancer-related deaths, making early detection and classification vital for patient survival. Among its types, non-small cell lung cancer (NSCLC) represents nearly 85% of cases, while small cell lung cancer (SCLC) accounts for the rest. The five-year survival rate remains below 20%, mainly due to the lack of early diagnosis. With the advent of medical imaging technologies like CT scans and PET scans, the potential for automated classification using artificial intelligence has gained significant traction, especially to assist radiologists in handling large volumes of patient data efficiently. In recent years, hybrid models combining deep learning for image-based feature extraction with powerful machine learning classifiers like XGBoost for decision-making have demonstrated remarkable improvements in diagnostic accuracy. These models allow for better generalization and interpretation by learning complex features from image data while leveraging the robustness of gradient boosting frameworks. As healthcare systems worldwide strive for early detection tools that are not only accurate but also explainable, the integration of these technologies becomes indispensable in enhancing clinical decision-making processes for lung cancer diagnosis and treatment planning.

2. LITERATURE SURVEY

Al-Shouka and Alheeti employed transfer learning with VGG16, achieving high accuracy in detecting malignant tissues in CT images. Their approach demonstrated the efficiency of transfer learning in reducing computational complexity and enhancing reliability [1].

Bherje et al. proposed a deep learning framework for predicting lung cancer using CT scan images, achieving an average accuracy of 72.41%. Their study demonstrated the potential of deploying CNN-based systems in practical settings for early cancer detection [2].

Kapoor et al. explored the effectiveness of the pre-trained VGG16 model in detecting lung cancer from histopathological images. Their study utilized publicly available datasets to train and assess the model’s performance, demonstrating that VGG16 could accurately classify lung tissue into benign, normal, or malignant categories. This study confirmed the model’s potential for reliable lung cancer detection, emphasizing its ability to handle complex histopathological data and enhance diagnostic precision [3].

Huang et al. applied the VGG16 model to classify CT images of lungs into three categories: benign, normal, and malignant. The study highlighted VGG16’s robustness, evaluating it against adversarial attacks to ensure stability and accuracy. Their findings reinforced VGG16’s suitability for handling CT scans in clinical settings, demonstrating its ability to differentiate between various lung conditions effectively [4].

Xu compared traditional CNN models with more advanced architectures, including VGG16, for non-small cell lung cancer classification. While basic CNNs achieved acceptable accuracy, VGG16 outperformed them regarding learning efficiency and overall accuracy, proving that deeper networks yield better diagnostic results when applied to lung cancer datasets. This study supports using pre-trained CNNs like VGG16 in lung cancer diagnosis, emphasizing their superior performance and feature extraction capabilities [5].

Tejaswini et al. analyzed different CNN architectures for lung cancer detection, focusing on feature extraction and machine learning algorithms. Their research demonstrated that CNNs, including VGG16, significantly improve diagnostic accuracy compared to conventional methods. The study concluded that VGG16’s deep architecture allows for a more precise analysis of lung tissues, making it a suitable choice for early lung cancer detection [6].

A broader comparison by V et al. assessed various 3D CNN models, such as AlexNet, CNN-T5, and VGG16, in classifying lung cancer using CT and PET scans. VGG16 emerged as a highly accurate model due to its structured architecture and ability to adapt through transfer learning, further establishing its applicability in lung cancer diagnosis. The study also emphasized optimizing hyperparameters like image and batch sizes to enhance model performance [7].

Karthikeyan et al. applied deep learning to classify CT scan images of lungs into benign and malignant categories. Their VGG16-based model achieved significant accuracy, underscoring its capability to reduce diagnostic delays and improve early detection [8].

3. PROPOSED METHODOLOGY

The lung cancer detection framework leverages a combination of traditional machine learning, deep neural networks, and a hybrid model to provide a robust, accurate, and versatile diagnostic tool. By integrating multiple approaches, it balances simplicity and computational efficiency with the ability to capture complex patterns in CT images. The use of the hybrid CNN and XGBoost model enhances feature extraction and classification power, leading to improved prediction accuracy compared to standalone methods. The modular design allows the system to be adaptable for different datasets or related medical image classification tasks, making it highly applicable to varied clinical scenarios. Furthermore, the pipeline's inclusion of comprehensive metric calculations ensures thorough evaluation, enabling clinicians or researchers to assess model reliability effectively.

Step 1: Dataset Acquisition The process begins with the collection of lung cancer CT images. These images form the input dataset, representing various cases that will be used to train and test the models. Ensuring a high-quality, representative dataset is critical for reliable model performance.

Step 2: Image Processing Once the dataset is obtained, each CT image is read and resized to a standardized dimension suitable for the models. This normalization step ensures consistent input size, which is necessary for both machine learning and deep learning models. Additional preprocessing steps such as normalization or noise reduction may be applied here to enhance image quality.

Step 3: Train/Test Split The processed dataset is then divided into training and testing subsets, typically with an 80/20 ratio. The training set is used to train the models to recognize patterns associated with lung cancer, while the testing set is reserved to evaluate model performance on unseen data, ensuring generalizability.

Step 4: Model Training and Evaluation Three models are trained separately on the training data:

The existing machine learning model, Multinomial Naive Bayes, provides a baseline classification approach using statistical assumptions. The deep neural network (a feedforward neural network) learns hierarchical features directly from the image data through multiple processing layers. The hybrid model combines convolutional neural network (CNN) based feature extraction with the XGBoost classifier, which excels in handling complex data relationships and boosting classification accuracy.

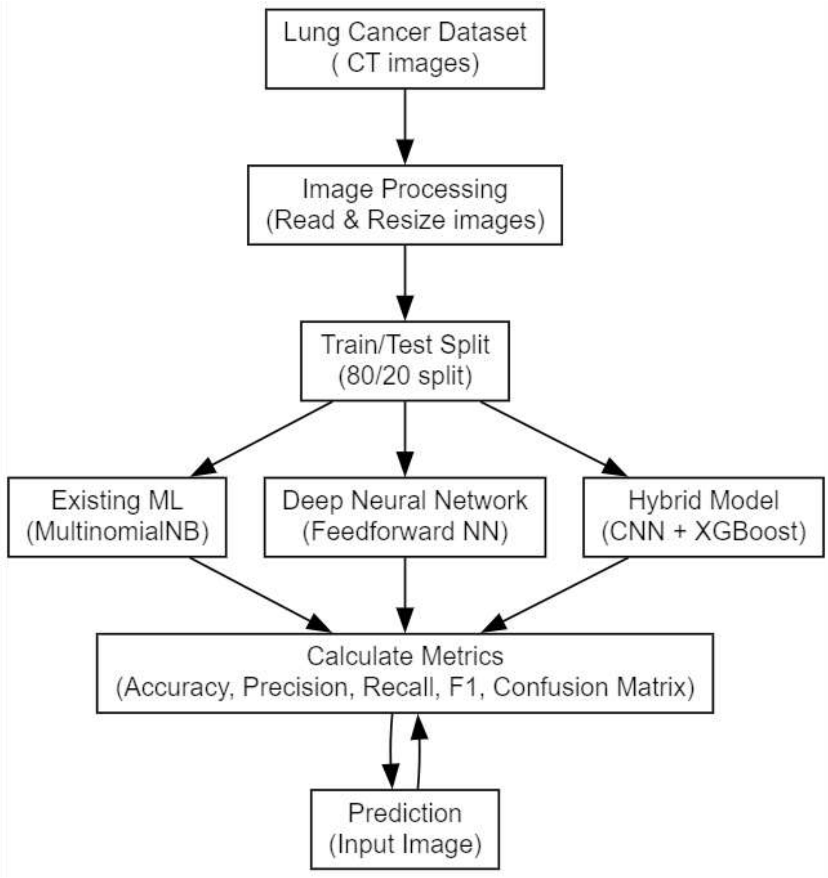


Fig. 1: Proposed System Architecture.

Step 5: Metrics Calculation After predictions are made by each model on the test set, performance metrics such as accuracy, precision, recall, F1 score, and the confusion matrix are calculated. These metrics offer detailed insights into each model's strengths and weaknesses, guiding decisions on model selection or further tuning.

Step 6: Prediction The final step involves using the trained models to predict the class of new input CT images. The system processes the new image through the same preprocessing pipeline, then uses the models to classify whether the image indicates lung cancer or not. Results are again validated through metric calculations to ensure consistent prediction quality.

CNN Feature Extraction

This convolutional neural network (CNN) architecture with transfer learning leverages the power of pretrained models (such as ResNet) combined with additional convolutional layers to efficiently extract hierarchical features from images. It benefits from pretrained weights, which accelerates training and improves performance even with limited data by using learned representations from large datasets. The stepwise pooling reduces spatial dimensions, preserving essential features while lowering computational load. The final dense layers enable flexible classification according to the number of output classes. This approach is well-suited for application-specific image classification tasks, such as medical imaging, where both accuracy and computational efficiency are critical. Moreover, saving the model structure and training history supports reproducibility and future fine-tuning.

Step 1: Model Initialization and Transfer Learning Setup The model starts by incorporating a pretrained network (e.g., ResNet) to benefit from its learned feature representations. This transfer learning step provides a robust feature extraction base, which can generalize well to the new dataset with fewer training epochs.

Step 2: Adding Convolutional and Pooling Layers Additional convolutional layers with ReLU activation are added on top of the pretrained base to fine-tune the network for the specific classification task. Each convolutional layer is followed by max-pooling, which progressively reduces the spatial dimensions of the feature maps while retaining important information. This process helps the model focus on the most relevant features and reduces overfitting.

Step 3: Flattening the Feature Maps After several convolution and pooling layers, the multidimensional feature maps are flattened into a one-dimensional vector. This step prepares the data for the fully connected layers by converting the spatial features into a format suitable for classification.

Step 4: Dense Layers for Classification The flattened vector is fed into a dense (fully connected) layer with ReLU activation to learn non-linear combinations of the extracted features. Finally, the output dense layer with softmax activation produces probabilities corresponding to each target class, enabling multiclass classification.

Step 5: Compilation and Training The model is compiled with an optimizer (Adam) and a loss function suitable for multiclass classification (categorical cross-entropy). It is then trained over multiple epochs on the training data, with validation data used to monitor performance and prevent overfitting. During training, the model adjusts its weights to minimize the loss and improve accuracy.

Step 6: Saving Model and Training History After training completes, the model's weights and architecture are saved separately, enabling future loading and deployment without retraining. Additionally, the training history containing metrics like accuracy and loss over epochs is saved for analysis, helping in performance evaluation and tuning.

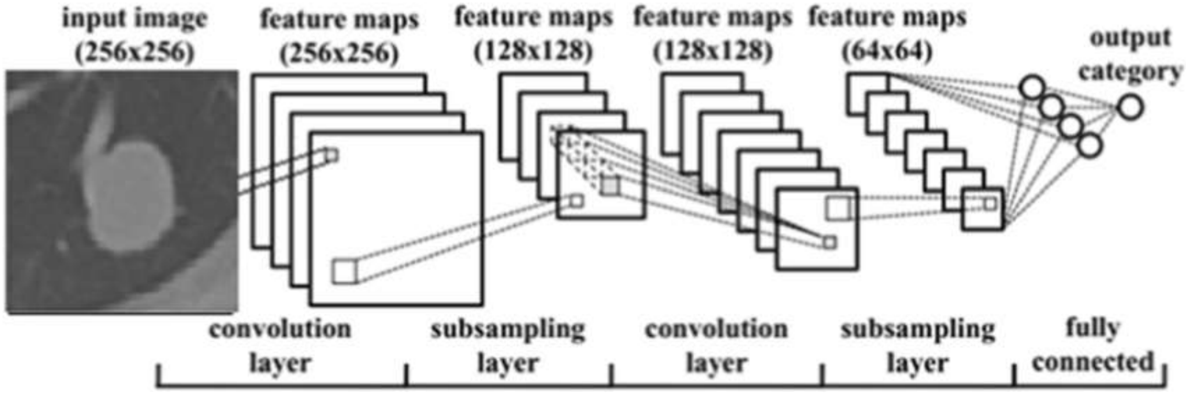


Fig. 2: CNN for Lung Cancer.

Fully Connected Layers

The SoftMax classifier is highly effective for multi-class classification tasks where the goal is to assign an input to one specific class among many. Its main advantage is that it converts the output of a neural network into a probability distribution over predefined target classes, making it suitable for decision-making tasks in image-based applications. Unlike binary classification techniques, SoftMax ensures that the sum of all output probabilities equals one, which enhances interpretability. It is not suitable for random or unrelated image input, as such data can lead to misclassification due to the lack of relevance to trained classes.

Figure 4.8 shows the Fully Connected layer architecture. The detailed procedure given as follows

Step 1: Receive Network Output Vector The classifier receives a vector of raw scores (logits) from the final dense layer of the neural network. Each score corresponds to a class, such as ‘Normal’ or ‘Tamper’ in forgery detection.

Step 2: Exponential Transformation Each logit in the output vector is exponentiated to convert all scores to positive values. This step amplifies differences between scores while preserving their relative ordering.

Step 3: Compute the Denominator The sum of all exponentiated logits is computed. This value is used to normalize the output scores and ensure that the final result forms a probability distribution.

Step 4: Normalize the Scores Each exponentiated logit is divided by the sum of exponentiated logits. This gives a final score for each class, representing the predicted probability that the input belongs to that class.

Step 5: Class Selection The class with the highest probability is selected as the final prediction. For example, if the ‘Tamper’ class has a higher probability than ‘Normal’, the image is labeled as tampered.

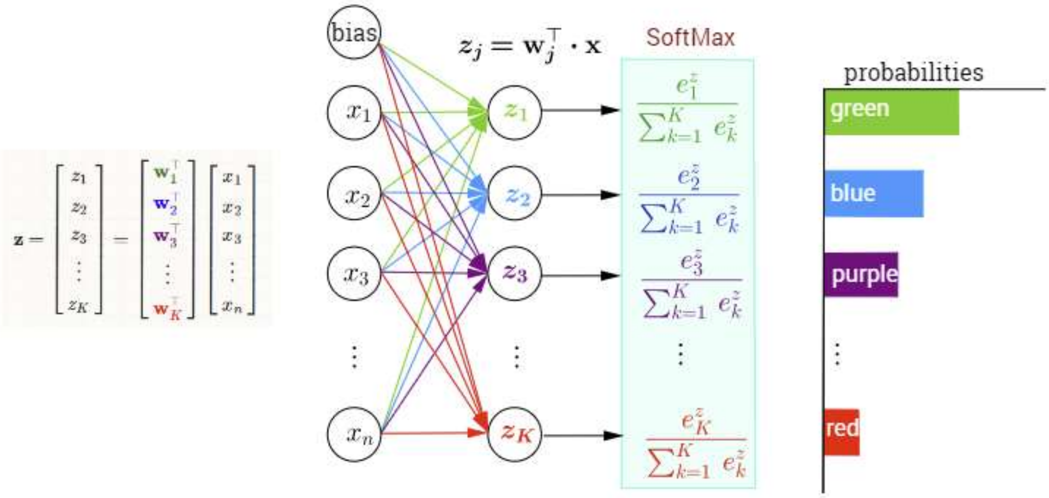


Fig. 3: Fully Connected Layer with SoftMax classifier

Advantages

Hierarchical Feature Learning: CNNs can automatically learn hierarchical representations of data. They extract low-level features like edges and textures in earlier layers and progressively learn more abstract and complex features in deeper layers. This hierarchical approach enables CNNs to effectively capture the intricate structures and patterns present in images and other forms of data.

Translation Invariance: CNNs leverage convolutional operations and pooling layers to achieve translation invariance, meaning they can recognize patterns regardless of their location in the input space. This property makes CNNs robust to translations, rotations, and other transformations in the input data, enhancing their generalization ability.

Parameter Sharing: CNNs utilize weight sharing across spatial locations, reducing the number of parameters compared to fully connected networks. By sharing parameters, CNNs can efficiently learn from large datasets and generalize well to unseen data without overfitting.

Sparse Connectivity: In CNNs, neurons in each layer are only connected to a small region of the input volume, as determined by the receptive field size of the convolutional filters. This sparse connectivity reduces the computational burden and memory requirements of the network, enabling efficient processing of high-dimensional data such as images and videos.

Local Receptive Fields: CNNs exploit local connectivity and receptive fields to capture spatial dependencies and local patterns within the input data. By focusing on small regions of the input at a time, CNNs can effectively extract features while preserving spatial information, enabling them to handle complex tasks like object recognition and segmentation.

State-of-the-Art Performance: CNNs have demonstrated state-of-the-art performance across a wide range of computer vision tasks, including image classification, object detection, semantic segmentation, and image generation. Their ability to learn hierarchical representations and leverage spatial relationships within data makes them indispensable in many real-world applications.

4. RESULTS AND DISCUSSION

The confusion matrix in Figure 4 for the NBC model visually represents its classification performance across the 180 test samples. It shows the number of correct and incorrect predictions for each class (adenocarcinoma, large cell carcinoma, normal, squamous cell carcinoma). The matrix highlights the model's poor performance, with significant misclassifications, particularly for adenocarcinoma (low recall of 0.24), contributing to the overall low accuracy of 47.22%.

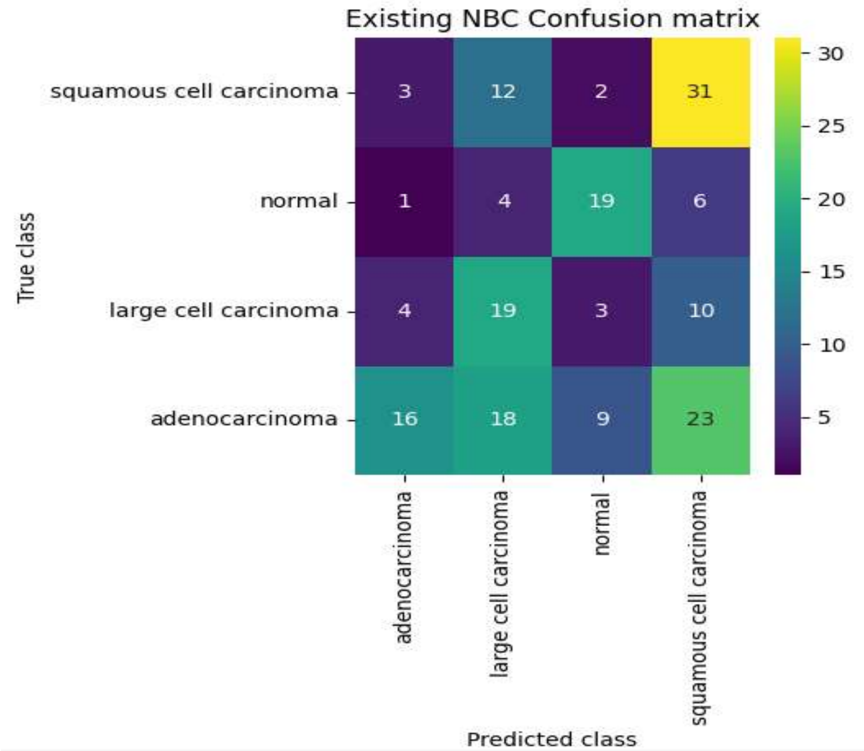


Fig. 4: Confusion matrix of NBC.

This figure 5 reports the Deep Neural Network (DNN) performance, achieving a much higher accuracy of 90.56%, precision of 92.26%, recall of 90.47%, F1-score of 91.07%, sensitivity of 100%, and specificity of 80%. The classification report indicates strong performance across classes: adenocarcinoma (0.86, 0.92, 0.89), large cell carcinoma (0.97, 0.78, 0.86), normal (0.97, 1.00, 0.98), and squamous cell carcinoma (0.90, 0.92, 0.91). The DNN significantly outperforms NBC, particularly in sensitivity and class-specific metrics "

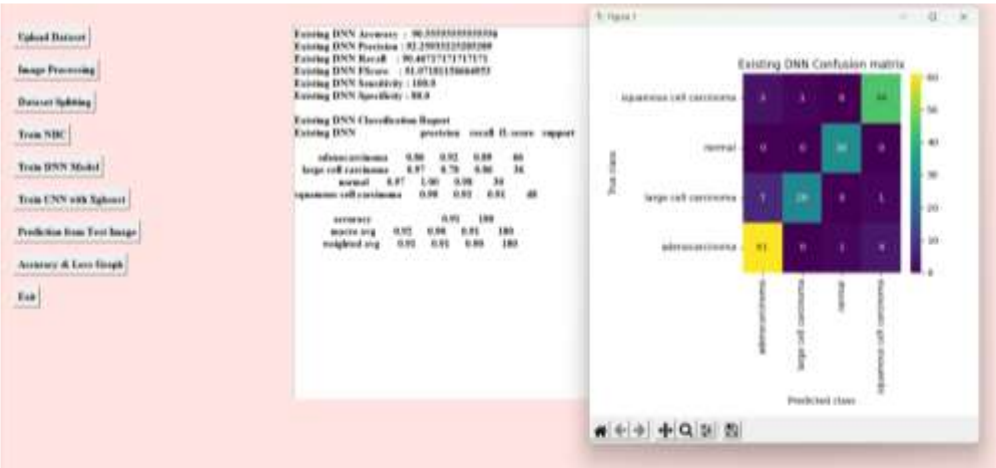


Fig. 5: Existing DNN Performance.

Figure 6 presents the performance of the CNN with XGBoost model, achieving an accuracy of 91.11%, precision of 93.52%, recall of 90.42%, F1-score of 91.75%, sensitivity of 98.70%, and specificity of 88.46%. The classification report shows excellent class-specific results: adenocarcinoma (0.87, 0.96, 0.92), large cell carcinoma (0.96, 0.82, 0.88), normal (1.00, 1.00, 1.00), and squamous cell carcinoma (0.91, 0.83, 0.87). This model slightly outperforms the DNN, particularly in specificity and normal class detection.

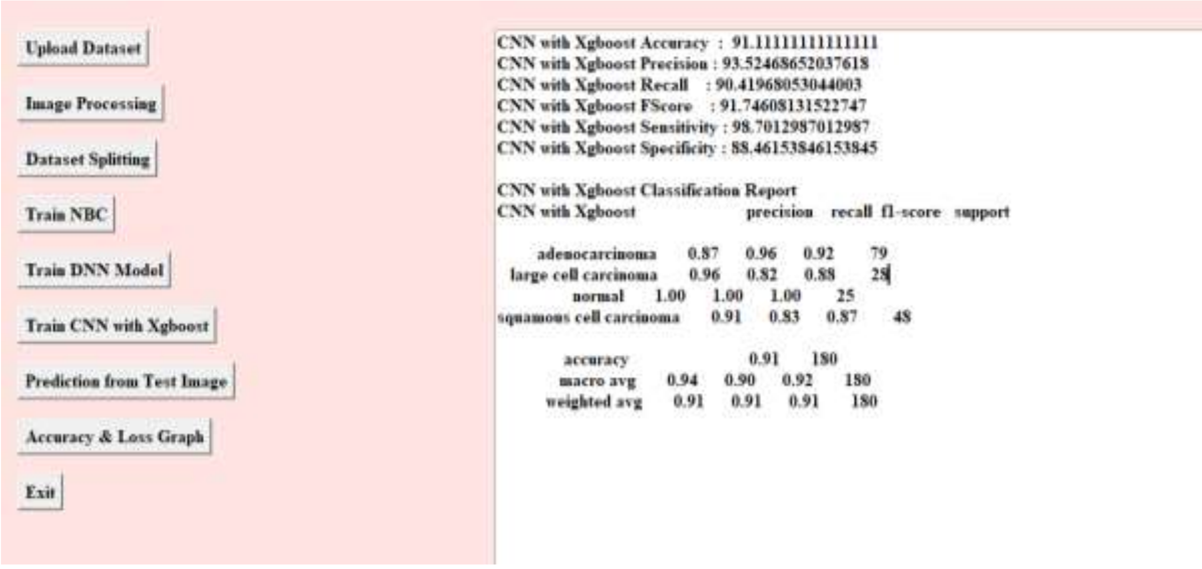


Fig. 6: Performance evaluation of CNN with XGboost Classifier

This figure 7 shows the confusion matrix for the CNN with XGBoost model, illustrating its classification performance across the 180 test samples. The matrix likely shows fewer misclassifications compared to NBC, with strong performance for the normal class (perfect precision and recall) and improved predictions for adenocarcinoma and squamous cell carcinoma, aligning with the high accuracy of 91.11%.

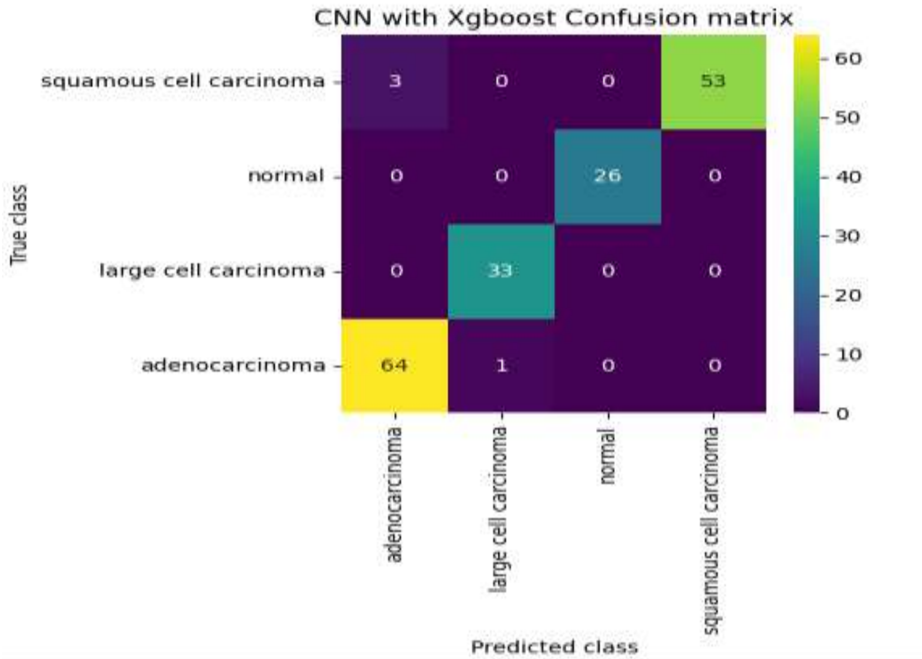
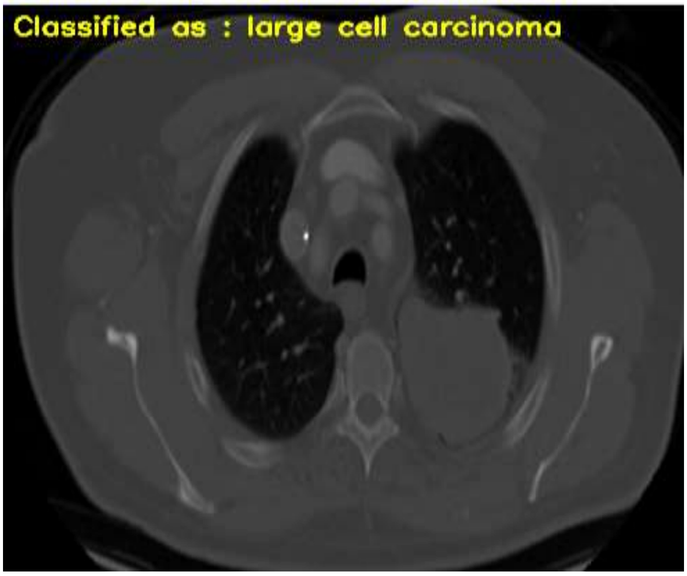
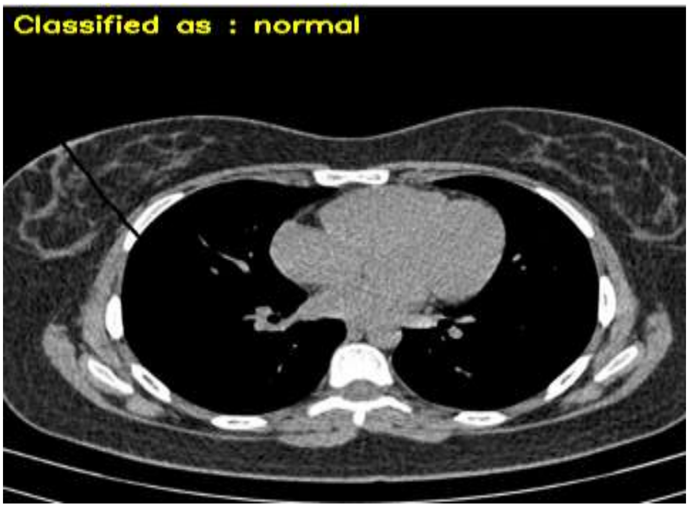


Fig. 7: Confusion matrix of Proposed CNN Model


Classified as : adenocarcinoma


Classified as : large cell carcinoma


Classified as : normal

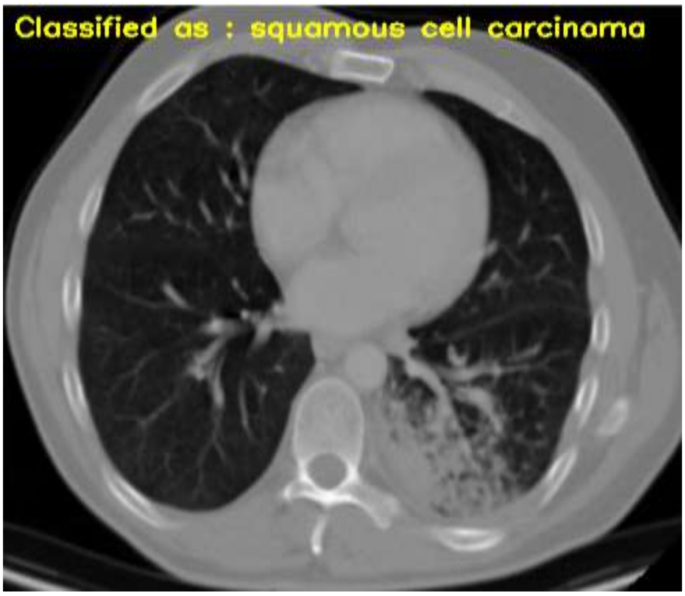


Fig. 8: Predicted output using CNN with XGBoost model

Figure 8 displays sample predictions from the CNN with XGBoost model, likely showing input images alongside their predicted class labels (e.g., adenocarcinoma, normal) and confidence scores. This figure demonstrates the model's practical application, highlighting its ability to accurately classify lung cancer types based on preprocessed images.

5. CONCLUSIONS

The analysis of the lung cancer detection dataset, comprising 900 images across four classes (adenocarcinoma, large cell carcinoma, normal, and squamous cell carcinoma), reveals significant differences in the performance of the three evaluated models: Naive Bayes Classifier (NBC), Deep Neural Network (DNN), and Convolutional Neural Network (CNN) with XGBoost. The NBC model exhibited poor performance, with an accuracy of 47.22%, precision of 51.09%, recall of 51.23%, and F1-score of 47.78%, struggling particularly with adenocarcinoma (recall: 0.24) and large cell carcinoma (precision: 0.36). This indicates its inadequacy for complex image-based classification tasks. In contrast, the DNN model achieved a robust accuracy of 90.56%, with high sensitivity (100%) and strong class-specific performance, notably for the normal class (F1-score: 0.98). The CNN with XGBoost model slightly outperformed the DNN, achieving an accuracy of 91.11%, precision of 93.52%, and an F1-score of 91.75%, with perfect classification for the normal class (F1-score: 1.00) and excellent results for adenocarcinoma (F1-score: 0.92). The superior performance of the CNN with XGBoost is attributed to its ability to extract intricate image features and leverage XGBoost's ensemble learning for classification. The confusion matrices and training/validation graphs further confirm the CNN with XGBoost's robustness, with minimal misclassifications and stable learning curves. Overall, the CNN with XGBoost model demonstrates the highest reliability for lung cancer detection, making it a promising tool for medical image analysis, though slight variations in class-specific performance (e.g., lower recall for squamous cell carcinoma) suggest room for further optimization.

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