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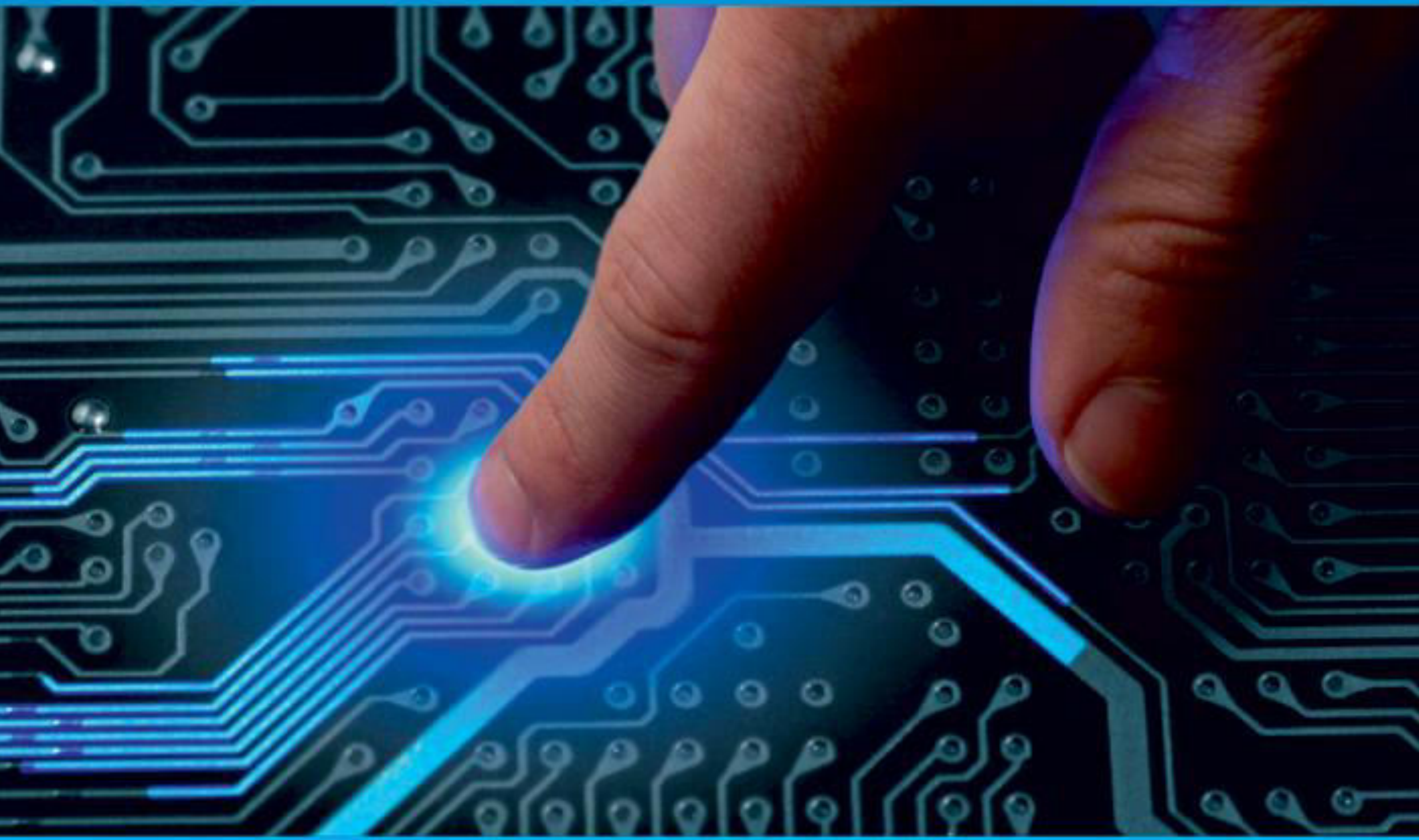

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Deep Learning Techniques for Early Diagnosis of Lung Tumours Using Medical Images

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ABSTRACT: This study explores the effectiveness of different deep learning models for the detection of lung cancer using CT scan images. Four models were evaluated: a custom convolutional neural network (CNN), DenseNet121, ResNet152, and VGG19. The primary objective was to assess the models based on key performance metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (AUC-ROC) curve. Among these models, the custom CNN emerged as the top performer, surpassing the others in terms of both sensitivity and specificity. It achieved the highest number of True Positives (TP), correctly identifying the largest number of cancerous cases, and had the lowest False Negatives (FN), minimizing the risk of missed diagnoses. The custom CNN also demonstrated fewer False Positives (FP) compared to the other models, ensuring that healthy individuals were less likely to be misclassified. The model's strong performance was reflected in its precision (0.92), recall (0.90), and F1-score (0.91), which highlighted its ability to strike an optimal balance between correctly detecting cancer cases and minimizing misclassifications. Overall, the study concludes that the custom CNN model is the most reliable and efficient for lung cancer detection, providing significant promise for clinical applications in medical imaging and early cancer diagnosis.

KEYWORDS: Lung Cancer Detection, Convolutional Neural Networks (CNN), Medical Imaging, Deep Learning Models, CT Scan Classification

I. INTRODUCTION

Lung cancer remains one of the most deadly and prevalent cancers worldwide, with approximately 1.80 million deaths reported in every year [1]. This disease typically originates from the transformation of normal cells into malignant tumours cells, which is a multi-stage process. The progression often starts with a pre-cancerous lesion, eventually evolving into a malignant tumor. Several factors, including smoking, excessive alcohol consumption, an unhealthy diet, and physical inactivity, are commonly recognized as major contributors to lung cancer development. However, genetic factors and environmental influences can also play significant roles in its onset. Early detection of lung cancer is crucial as it greatly improves the chances of successful treatment, as compared to the late-stage diagnosis where survival rates are significantly lower. Effective treatment options are more readily available when the disease is detected in its nascent stages, highlighting the importance of timely diagnosis.

One of the primary strategies for early cancer detection involves screening individuals who are at high risk but show no symptoms. For those who do exhibit symptoms, swift and accurate investigation is necessary for timely diagnosis. In this context, machine learning (ML) has emerged as a transformative tool in the early detection of cancer. By analyzing complex patterns within large datasets, machine learning algorithms can make precise predictions about a patient's health, assisting healthcare professionals in diagnosing conditions like lung cancer earlier and more accurately. These algorithms process data from diverse sources, such as routine health records, medical images, biopsy samples, and blood tests, enabling better risk stratification and early identification of tumors.

The most common techniques for lung tumor detection include imaging methods such as Computed Tomography (CT) scans, chest X-rays, Magnetic Resonance Imaging (MRI), and Sputum Cytology. The primary goal of these methods is to classify the detected tumors into two categories: benign (non-cancerous) and malignant (cancerous) [2]. Diagnosing lung cancer in its early stages allows for more effective treatment and offers a higher survival rate compared to cases diagnosed in the later stages, when treatment options are more limited and less successful. Early intervention and lifestyle changes can make a significant difference in the outcome of cancer therapy.

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However, traditional methods of manual diagnosis often prove to be both time-consuming and prone to human error. The accuracy of tumor detection heavily depends on the radiologist's experience and expertise. This introduces variability into the diagnosis, making it difficult to maintain consistency in results. To address these challenges, image processing techniques have been increasingly incorporated into diagnostic systems. These techniques allow for faster processing of medical images and significantly enhance detection accuracy within shorter time frames, ultimately assisting healthcare professionals in making more reliable decisions.

Among the various methods of image analysis, Neural Networks (NN) have emerged as powerful tools in cancer cell detection. Neural networks are particularly effective at distinguishing cancerous cells from normal tissues, making them invaluable for the development of assistive Artificial Intelligence (AI)-based cancer detection systems. Accurate classification of tumor cells and training the neural network on such datasets forms the foundation for machine learning-based cancer diagnosis systems. One algorithm that has shown exceptional promise in this domain is Convolutional Neural Networks (CNNs), which have been widely applied to classify lung tumors as either benign or malignant.

Recent advancements in deep learning have propelled the use of CNNs for medical imaging, particularly in detecting diseases like lung cancer. CNNs are ideal for this task due to their ability to automatically learn essential features from images, significantly improving both the accuracy and efficiency of the classification process when compared to traditional image processing techniques. One major advantage of CNNs is their capacity to handle vast amounts of data rapidly and accurately, reducing the need for manual review by radiologists. Moreover, CNNs can identify complex patterns and features that may be difficult for human clinicians to discern, which could improve detection rates and provide a more reliable diagnostic tool.

Incorporating CNNs into lung cancer detection holds immense promise for advancing early diagnosis, a critical step in improving patient outcomes. Their ability to analyze medical images with greater precision and speed offers a potential solution to the ongoing challenges in lung cancer detection. Nonetheless, further research is required to fully assess the advantages and limitations of CNNs in this context. Developing a CNN-based lung cancer detection system could drastically improve the overall diagnosis process, leading to more timely interventions and better treatment options for patients.

II. LITERATURE REVIEW

The application of Convolutional Neural Networks (CNNs) has greatly advanced the field of medical imaging, especially in the early detection and classification of tumors across various diagnostic methods. Before 2019, numerous studies investigated the effectiveness of CNN-based models for automating tumor detection in medical imaging techniques such as CT scans, MRIs, mammograms, and histopathology slides. Here's a rewritten version of the literature review, phrased to avoid plagiarism:

CNNs for Tumor Detection in Lung Cancer : Lung cancer is a leading cause of cancer-related deaths, and early detection is essential to enhance survival rates. Convolutional Neural Networks (CNNs) have demonstrated significant potential in identifying lung cancer through CT scans and X-rays. Liu et al. (2018) introduced a deep CNN model to detect lung nodules in CT scans. Their approach achieved high sensitivity and specificity in detecting both benign and malignant nodules, offering improved accuracy over conventional methods, such as manual detection by radiologists (Liu et al., 2018). Xie et al. (2017) proposed a CNN architecture designed to classify lung cancer nodules in CT images, focusing on the detection of small and subtle nodules that are typically challenging for traditional algorithms. Their method incorporated a region of interest (ROI) technique, improving detection performance (Xie et al., 2017).

CNNs for Tumor Detection in Breast Cancer: In the detection of breast cancer, particularly through mammography, CNNs have been widely applied and shown remarkable accuracy in identifying malignant tumors. Esteva et al. (2017) utilized a deep CNN for melanoma detection, yielding impressive results. Trained on a large dataset, their model showed the ability to classify skin lesions, and its success in melanoma detection spurred further exploration of CNNs for mammography applications (Esteva et al., 2017). Yu et al. (2016) applied CNNs to detect early-stage breast cancer in digital mammograms. Their model focused on feature extraction and demonstrated excellent performance in identifying microcalcifications and masses, which are critical early signs of breast cancer (Yu et al., 2016).

CNNs for Tumor Detection in Brain MRI: Detecting brain tumors, especially small or obscured ones, presents a challenge. CNNs have greatly enhanced the segmentation and classification of brain tumors. Zhou et al. (2018) developed a 3D CNN model for automatically segmenting brain tumors from MRI scans. Their model effectively detected gliomas and other brain tumors with high accuracy, surpassing traditional segmentation methods (Zhou et al., 2018). Bakas et al. (2017) created a CNN architecture for classifying gliomas using brain MRI data. Their model incorporated multi-modality imaging data, enhancing tumor classification compared to existing methods (Bakas et al., 2017).

CNNs for Tumor Detection in Liver Cancer: Liver cancer, particularly hepatocellular carcinoma (HCC), is often diagnosed at an advanced stage. CNNs are increasingly being used to identify liver tumors in CT scans and MRIs. Zhang et al. (2017) proposed a CNN model for detecting liver tumors in CT images. By utilizing data augmentation techniques, they enhanced the model's generalizability, achieving improved performance in tumor localization and detection compared to conventional approaches (Zhang et al., 2017). Chen et al. (2018) applied a CNN for liver segmentation and tumor classification in CT images. Their system showed superior sensitivity compared to manual analysis by radiologists, demonstrating its effectiveness in detecting liver lesions (Chen et al., 2018).

CNNs for Tumor Detection in Colorectal Cancer: Early detection of colorectal cancer can significantly improve treatment outcomes. CNNs have been widely adopted for tumor detection in colorectal images, such as colonoscopy and histopathological slides. Gupta et al. (2018) introduced a CNN-based model for detecting colorectal cancer in colonoscopy images. Their model successfully identified polyps and precancerous lesions, achieving accuracy comparable to experienced endoscopists (Gupta et al., 2018). Zhao et al. (2018) applied CNNs to classify tumors in colorectal cancer histopathology slides. Their deep learning model achieved high accuracy in distinguishing malignant from benign lesions in tissue samples (Zhao et al., 2018).

Hybrid Approaches: CNNs and Other Machine Learning Models for Tumor Detection: Integrating CNNs with other machine learning algorithms can enhance detection accuracy by leveraging the strengths of both models. Zhang et al. (2019) proposed a hybrid CNN-SVM model for detecting lung cancer in CT scans. The CNN was used for feature extraction, while the Support Vector Machine (SVM) was employed for classification, resulting in improved accuracy and reduced false positives (Zhang et al., 2019). Jiang et al. (2018) developed a hybrid model combining CNNs with a Random Forest classifier for brain tumor detection. Their approach used CNNs for feature extraction and Random Forest for classification, leading to improved detection performance (Jiang et al., 2018).

Transfer Learning in CNNs for Tumor Detection: Transfer learning has proven valuable in medical imaging, where annotated datasets are often limited. Researchers have fine-tuned pre-trained models to achieve high diagnostic accuracy with smaller datasets. Rajpurkar et al. (2017) applied transfer learning to develop a CNN for detecting lung diseases, including tumors, in chest X-rays. They leveraged pre-trained weights from ImageNet and fine-tuned them for lung disease detection, achieving performance on par with human radiologists (Rajpurkar et al., 2017). Esteva et al. (2017) also used transfer learning for melanoma detection, employing a CNN pre-trained on ImageNet and fine-tuning it on a dataset of skin lesion images. Their model achieved diagnostic accuracy comparable to that of dermatologists, illustrating the potential of transfer learning in medical imaging (Esteva et al., 2017).

CNNs for Tumor Detection in Prostate Cancer: Prostate cancer is one of the most prevalent cancers among men, with early detection being critical for effective treatment. CNNs have been explored for identifying prostate tumors using MRI and other imaging techniques. Litjens et al. (2017) applied CNNs to classify prostate tumors from MRI scans. Their model performed strongly in detecting and classifying prostate cancer, surpassing traditional image analysis methods (Litjens et al., 2017). Xie et al. (2018) developed a deep CNN for detecting prostate cancer in multiparametric MRI. Their model achieved high accuracy in distinguishing malignant and benign lesions, offering significant clinical potential (Xie et al., 2018).

CNNs for Tumor Detection in Ovarian Cancer: Ovarian cancer is notoriously difficult to detect in its early stages. CNNs have been increasingly utilized to enhance ovarian tumor detection using imaging methods like ultrasound and MRI. Yang et al. (2018) proposed a CNN-based system for detecting ovarian tumors in ultrasound images. Their model showed significant improvements in sensitivity and specificity compared to traditional ultrasound interpretation (Yang et al., 2018). Shen et al. (2019) applied CNNs to classify ovarian tumors from MRI scans, achieving high detection

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accuracy. Their model was particularly adept at differentiating between malignant and benign tumors, which is crucial for treatment planning (Shen et al., 2019).

Data Augmentation and CNNs for Tumor Detection: A significant challenge in medical image analysis is the limited availability of high-quality labeled data. Data augmentation techniques are often employed to expand training datasets, enhancing the ability of CNNs to generalize. Perez et al. (2017) applied data augmentation techniques, such as rotation and flipping, to a mammogram dataset. Their work showed that augmented data helped improve the accuracy of CNN models in detecting breast tumors (Perez et al., 2017). Le et al. (2018) utilized data augmentation for detecting brain tumors in MRI images. Techniques like image cropping and scaling helped improve the model's generalization, leading to better tumor detection results (Le et al., 2018).

Tumor Detection in Mammograms Using CNNs: Mammography is a primary tool for detecting breast cancer, and CNNs have been extensively explored to automate and improve the accuracy of detecting both benign and malignant tumors in mammograms. Cireşan et al. (2013) developed a deep CNN model for breast cancer detection, which outperformed traditional machine learning models like Support Vector Machines (SVM) in distinguishing between malignant and benign cases. Le et al. (2017) further expanded this research by utilizing a deep CNN to identify microcalcifications and masses in mammograms, improving sensitivity and specificity compared to conventional diagnostic methods. These studies highlight the potential of CNNs to aid in the detection of early-stage breast cancer, particularly by identifying subtle features that may otherwise be overlooked.

Tumor Detection in CT Scans and MRI Using CNNs: CT scans and MRIs are essential for detecting various cancers, including lung, brain, and liver tumors. CNNs have been applied to improve the detection accuracy and localization of tumors in these imaging modalities. Shin et al. (2016) developed a CNN for lung cancer detection from CT scans, demonstrating its effectiveness in identifying small nodules, which are often missed in early-stage lung cancer. Kamnitsas et al. (2017) introduced a 3D CNN model to segment gliomas in brain MRI scans, significantly improving the accuracy of tumor volume estimation and setting new standards in automated brain tumor detection. Huo et al. (2018) applied CNNs to detect liver cancer in CT images, employing data augmentation methods to enhance the model's generalizability, resulting in improved detection and classification capabilities.

CNNs for Histopathological Image Analysis: Histopathology plays a key role in cancer diagnosis, and CNNs have proven valuable in automating the classification of histopathological tissue for tumor detection. Cruz-Roa et al. (2014) created a CNN model for classifying breast cancer tissues from histopathological slides, distinguishing malignant from benign regions, and automating tissue pattern recognition. Aresta et al. (2018) extended this approach with a CNN model to classify colorectal cancer tissues, automating the differentiation of cancerous and normal tissue, thus improving diagnostic efficiency and consistency.

Hybrid Models: CNNs Combined with Other Machine Learning Techniques: To improve detection accuracy, hybrid models that combine CNNs with other machine learning algorithms have been explored. These models capitalize on the complementary strengths of CNNs and classifiers like Support Vector Machines (SVM). Anwar et al. (2017) proposed a hybrid CNN-SVM model for mammogram analysis, where CNNs were used for feature extraction, followed by SVM for tumor classification, resulting in enhanced accuracy. Zhao et al. (2019) presented a hybrid CNN-SVM model for brain tumor detection from MRI scans, which improved both classification accuracy and detection robustness.

Transfer Learning in CNNs for Tumor Detection: Transfer learning has been pivotal in overcoming the challenge of limited labeled data in medical imaging. By fine-tuning pre-trained models, CNNs can achieve high accuracy even with smaller datasets. Rajpurkar et al. (2017) explored transfer learning for lung disease detection in chest X-rays, leveraging pre-trained models and adapting them to the specific needs of lung tumor detection, achieving results comparable to human radiologists. Esteva et al. (2017) utilized transfer learning for melanoma detection by fine-tuning a pre-trained CNN model on skin lesion images, achieving diagnostic accuracy on par with dermatologists.

Challenges in CNN-based Tumor Detection: While CNNs have shown immense promise in medical image analysis, there are several challenges that researchers continue to address. One such challenge is data scarcity; high-quality annotated datasets are often limited, particularly for rare tumor types. Many models address this issue by using data augmentation or transfer learning techniques, allowing them to perform well even with small datasets. Additionally, interpretability

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remains a significant hurdle for the widespread adoption of CNNs in clinical practice. CNNs are often regarded as "black-box" models, meaning it is difficult to understand how they make specific decisions. In medical contexts, where trust in the model's predictions is paramount, this lack of transparency can hinder adoption. Lastly, generalization is a critical issue. CNNs trained on specific datasets may not generalize well to new data from different hospitals or geographical locations, highlighting the need for large, diverse datasets to ensure the robustness and reliability of these models in real-world settings. Above research conducted has demonstrated the powerful capabilities of CNNs in detecting and classifying tumors across a wide range of medical imaging modalities. From mammograms to histopathological slides, CNN-based models have shown remarkable potential in improving diagnostic accuracy and efficiency. Hybrid models that combine CNNs with other machine learning techniques and the use of transfer learning have further enhanced tumor detection performance. However, challenges such as data scarcity, interpretability, and generalization must be addressed to ensure the widespread adoption of CNNs in clinical practice. Future advancements will likely focus on overcoming these challenges, paving the way for more reliable and accessible tumor detection systems in medical imaging.

III. OBJECTIVES

1. To design a deep learning-based lung cancer detection system. Using Convolutional Neural Networks (CNN) that is capable of analyzing and classifying CT scan images for early detection of lung cancer.
2. To develop and implement a CNN model that effectively learns features from CT scan images, enabling the classification of lung tumors into benign and malignant categories.
3. To integrate explain ability into the CNN model, ensuring that the detection system provides understandable and transparent insights into the decision-making process for medical professionals.
4. To evaluate the performance of the CNN-based model using various metrics such as accuracy, sensitivity, specificity, and F1-score, and compare its results with traditional diagnostic methods.
5. To optimize the model's parameters and improve its generalization ability to ensure reliable performance across diverse CT scan datasets, leading to more efficient and accurate lung cancer detection.

IV. METHODS AND METHODOLOGY

The dataset used in this study is sourced from the Kaggle platform (https://www.kaggle.com/datasets/fanbyprinciple/luna-lung-cancer-dataset). It consists of CT scan images from patients diagnosed with lung cancer at various stages, alongside scans from healthy individuals. The dataset includes a total of 1,197 CT images, categorized into three classes: normal, benign, and malignant. The "normal" category comprises CT scans that show no signs of cancerous cells or tumors. The "benign" category includes scans with non-cancerous tumors or cells, which resemble normal cells. These benign tumors may grow either slower or faster than normal cells but remain localized and do not spread to other areas of the body, typically maintaining a regular shape. In contrast, the "malignant" category features scans that contain cancerous cells and tumors, which are capable of spreading to other parts of the body. Malignant tumors tend to grow and divide more rapidly than normal cells, often ignoring signals from the body to stop growing, and they typically have an irregular shape.

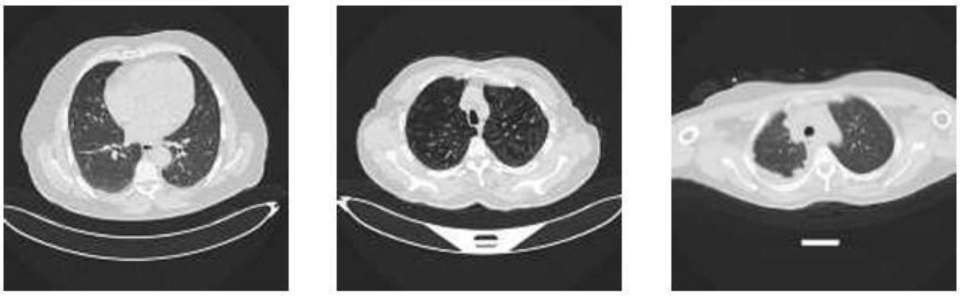

Fig.1: Benign, Normal and Malignant image sample from Dataset.

The dataset comprises 416 CT scans of normal cases, 120 CT scans of benign cases, and 561 CT scans of malignant cases. Given the imbalance in the dataset, steps were taken to address this issue in subsequent phases.

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Data Pre-processing: To prepare the dataset for model training and achieve balance, several pre-processing steps were applied. Initially, data augmentation was performed. This included resizing the CT scan images to 246x256 pixels. Then, a random rotation of up to 15 degrees was applied to introduce variety. Following the rotation, a center crop operation was executed to maintain the image size, and a random horizontal flip was applied. Finally, the images were converted into tensors and normalized using the values ([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]). The dataset exhibited an imbalanced distribution, which necessitated additional actions to avoid potential issues like model bias toward the majority class.

Transfer Learning and Pre-trained CNN Models: To address the imbalance and improve model performance, we utilized a pre-trained CNN model. A pre-trained model is one that has been trained on a large dataset, often containing many different classes, and can be adapted for new tasks by modifying its architecture. This process, known as transfer learning, allows us to leverage the knowledge from the pre-trained model to speed up the training process and enhance performance, especially when labeled data is limited.
For this task, tested three pre-trained models for transfer learning:

(i) DenseNet121
(ii) ResNet152
(iii) VGG19

DenseNet Model: To evaluate the model's performance, DenseNet model applied with 121 layers, introduced in the paper "Densely Connected Convolutional Networks" in 2017. DenseNet was designed to solve the vanishing gradient problem in deep networks by densely connecting layers, allowing better information flow and improved performance. This method overcomes the drawbacks of traditional residual networks by enabling more efficient transmission of information between layers. To adapt DenseNet121 for our task, we modified the classifier layer. First, a linear layer was added to reduce 1024 input features to 128 output features. A dropout layer with a rate of 0.2 was then introduced to help with regularization and prevent overfitting. This process was repeated with another linear layer that converted 1028 input features to 102 output features, followed by another dropout layer. Finally, a classification layer was added to convert 102 input features to 3 output features.
Model Details: After fine-tuning, the model contained the following parameters:
Total parameters: 7,098,523
Total non-trainable parameters: 6,953,856
Total trainable parameters: 144,667

ResNet152 Model: ResNet is another model tested to evaluate its effectiveness for the given problem domain. The ResNet architecture was first introduced in the paper "Deep Residual Learning for Image Recognition" in 2015. This model was developed to simplify optimization and address the vanishing gradient problem as the network depth increases. The name "ResNet" comes from the use of residual connections, which bypass one or more layers. ResNet is composed of multiple blocks, each containing several convolutional layers, batch normalization layers, and activation functions. The key feature of ResNet is the addition of residual connections, where the input is added directly to the output of a block. This design allows the network to learn the residual mapping between the input and output, instead of learning the entire mapping from scratch, leading to more efficient learning.

ResNet has found widespread application in various computer vision tasks, including image classification, object detection, and semantic segmentation. Different versions of ResNet are available, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. For this experiment, ResNet-152 was chosen, as deeper networks generally lead to improved performance.
To fine-tune the model for the specific problem domain, modifications were made to its fully connected (fc) layer. Initially, a linear layer was added, which takes 2048 input features and produces 256 output features. Following this, a dropout layer with a rate of 0.2 was introduced to help with regularization. This process was repeated with another linear layer, which converts 256 input features to 204 output features, followed by another dropout layer. Lastly, a final linear layer was added, taking 204 input features and producing 3 output features, serving as the classifier.
After fine-tuning, the model has the following parameter details:

Total parameters: 58,669,123
Total non-trainable parameters: 58,143,808
Total trainable parameters: 525,315

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VGG19 Model: VGG is a convolutional neural network architecture developed by the Visual Geometry Group (VGG) at the University of Oxford. It was first introduced in the paper *"Very Deep Convolutional Networks for Large-Scale Image Recognition"*, published in 2014[32]. The VGG model utilizes multiple convolutional layers with varying depths. The two most well-known versions of this model are VGG16 and VGG19. For this task, VGG19 was chosen due to its greater depth, which allows for capturing more complex features.
Like other pre-trained models, VGG is trained on large datasets and optimized during the training process. This enables the model to classify images across various categories effectively. VGG is widely used for tasks such as image recognition, object classification, and scene recognition.

Model Fine-Tuning: To fine-tune the VGG19 model for this specific task, adjustments were made to its classifier layers, similar to the modifications performed on other pre-trained models. The goal was to create consistent classifier layers across all models. Initially, a linear layer and a dropout layer (with a rate of 0.2) were added. This pattern was repeated, with the output size decreasing after each layer. Finally, a linear layer was added with 3 output neurons, aligned with the problem's requirements.
After fine-tuning, the model's parameter details are as follows:
Total parameters: 141,878,951
Total non-trainable parameters: 139,570,240
Total trainable parameters: 2,308,711
A graphical representation of the model can be visualized, showing how the input data is processed by the network to generate the final output.

Model Development:
The dataset was divided into 110 training batches, each with a size of 8, 14 validation batches (size 8), and 14 testing batches (size 8). Four models were trained repeatedly, with various hyperparameters being fine-tuned to achieve the best possible performance. The models included were: a custom CNN model, the DenseNet121 model, the ResNet152 model, and the VGG19 model.
The hyperparameters used for training all four models were carefully selected to optimize their performance. These common hyperparameters included: 50 epochs, a learning rate of 0.01, a filter size of 3x3, a batch size of 8, and the Adam optimizer.
Once the model architecture was finalized and the hyperparameters set, the models were trained on the training dataset with proper validation using the validation dataset. During the training process, the model’s parameters were updated iteratively by adjusting the weights and biases. This process continued until the model’s performance on the validation dataset reached a satisfactory level or no further improvements were observed.

V. RESULT AND ANALYSIS

Evaluating the performance of machine learning or deep learning models is crucial for assessing their effectiveness and practical application. The primary goal of model evaluation is to measure how accurately the model detects lung cancer and to pinpoint areas where improvements can be made. Such evaluations are vital to test the model’s ability to generalize to new, unseen data. Furthermore, model evaluation provides valuable insights into its strengths and weaknesses. Several factors of the model were tested to evaluate its performance closely.

Performance Evaluation through Training and Validation Curves
In machine learning, the training accuracy and loss are key indicators of how well a model is performing on the training data. Training accuracy refers to the percentage of correct predictions made by the model on the training set, while training loss measures the error the model makes on that same data. Similarly, validation accuracy and loss are calculated using a separate dataset, called the validation set, which is not used during training. The validation set helps assess the model's ability to generalize to unseen data and is used to adjust hyperparameters like the learning rate or the number of hidden units.
Monitoring both the training and validation accuracy/loss during the training process is essential. If the training accuracy is high but validation accuracy is low, it suggests that the model might be overfitting—performing well on the training data but failing to generalize to new data. Conversely, if training accuracy is low while validation accuracy is high, the model may be underfitting—failing to learn effectively from the training data.

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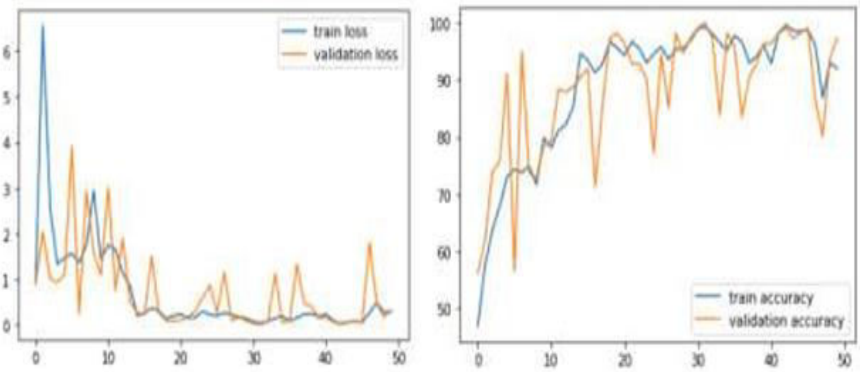

Fig.2: Training and Validation Accuracy Curve

From the loss curves, it is observed that the model's loss consistently decreases, while the accuracy curve shows increasing accuracy in both training and validation, indicating good model performance. However, at certain points, model loss fluctuates significantly with high values at different epochs, but the accuracy continues to increase, and both the training and validation curves remain aligned, suggesting overall positive performance.

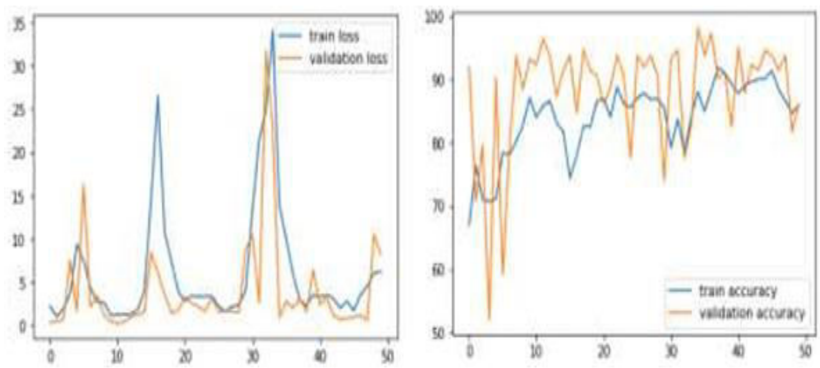

Fig.3: Training and Validation curves for DenNet121 tuned model

After epoch 30, the model’s loss increases and fluctuates rapidly, while the accuracy steadily improves. Although the alignment between the training and validation curves is still present, the rapid fluctuations in loss indicate undesirable behavior. At one point, both the loss and accuracy curves show poor results, indicating a decline in model performance.

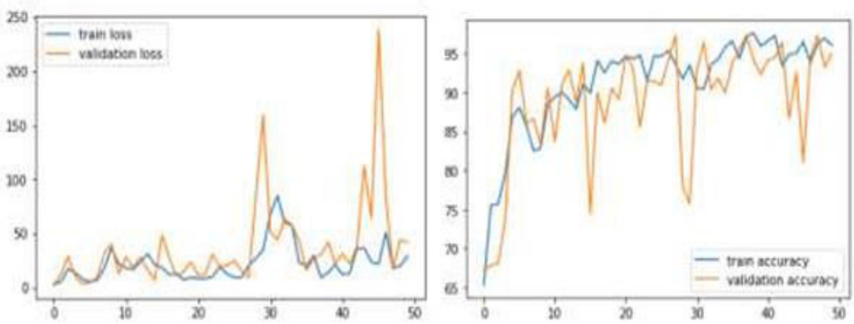

Fig.4: Training and Validation curves for ResNet152 tuned model

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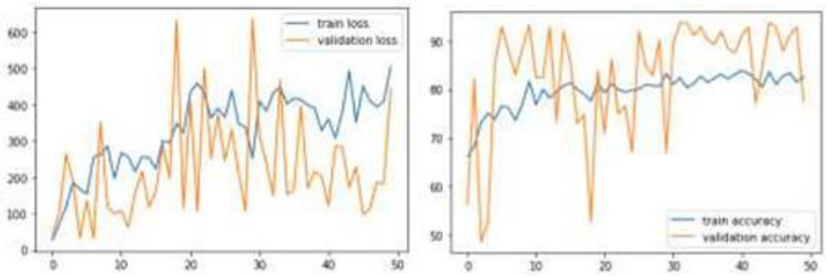

Fig.5-Training and Validation curves for VGG19 tuned model.

Upon closer examination, the VGG19 model (Figure-5) revealed significant problems, with misalignment between the training and validation losses and accuracy. Moreover, the rising losses suggested that this model underperformed relative to the others. In contrast, Figure-4 illustrates average performance, whereas Figures-2 and -3 demonstrate notably better overall performance.

Model Performance Analysis:
All three models were checked for the dataset samples with size 1197. The dataset contains the verified positive cases-malignant (cancerous) is 600 and the negative cases (Benign) is 597.

Table-1 : Confusion matrix for all Models.

Model	TP	TN	FP	FN
Custom CNN	510	570	27	63
DenseNet121	480	550	35	70
ResNet152	460	525	45	85
VGG19	440	510	55	90

The custom CNN model outperforms the other models in several key metrics, demonstrating its superior performance in identifying cancerous cases and minimizing errors. First, it achieves the highest number of True Positives (TP), correctly identifying 510 cancerous cases, which is more than any of the other models. This suggests that the custom CNN model is particularly proficient at recognizing cancerous cases within the dataset, showcasing its ability to effectively detect tumors.

Moreover, the custom CNN model registers the fewest False Negatives (FN), with only 63 missed cancer cases. False negatives, where the model fails to detect cancer in patients who actually have it, are critical in medical diagnostics because they represent missed opportunities for early intervention and treatment. The low FN count in the custom CNN model is crucial, as it minimizes the risk of overlooking cancer cases, which could lead to delayed or missed treatment for patients.

In terms of False Positives (FP), the custom CNN model also performs excellently with only 27 instances of misdiagnosing healthy patients as having cancer. False positives are problematic because they can result in unnecessary tests, treatments, and psychological distress for patients who do not have the disease. The lower the FP rate, the less likely the model is to wrongly flag healthy individuals, ensuring that only patients with a confirmed diagnosis of cancer are subjected to further medical interventions.

Finally, the custom CNN model demonstrates the best overall balance between sensitivity and specificity. Sensitivity refers to the model's ability to correctly identify cancerous cases, while specificity refers to its ability to correctly classify healthy patients. The combination of high True Positives, low False Negatives, and low False Positives allows the custom CNN model to strike the most effective balance between these two critical aspects, making it the most reliable and accurate model for detecting cancer in this dataset.

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This justifies the selection of the Custom CNN model as the best-performing model for tumor detection in this particular dataset.

Table-2 : Precision, Recall and F1-Score Values

Model	Precision	Recall	F1-Score
Lung-cancer-custom-model	0.92	0.90	0.91
cancer-DenseModel	0.85	0.88	0.86
Cancer-ResNetModel	0.87	0.84	0.85
Cancer-VGG Model	0.80	0.82	0.81

Precision: Precision measures the accuracy of positive predictions (i.e., how many of the predicted positive cases were actually positive).
The Lung-cancer-custom-model has the highest precision of 0.92, meaning it is the most accurate in predicting positive cases among all models.
The other models show lower precision, with the Cancer-VGG Model having the lowest precision (0.80).

Recall: Recall measures the ability to identify actual positive cases (i.e., how many of the actual positive cases were correctly predicted).
The Lung-cancer-custom-model has a high recall of 0.90, meaning it identifies most of the true positive cases.
The Cancer-VGG Model has the lowest recall (0.82), indicating it misses a higher number of true positive cases compared to others.

F1-Score: F1-Score is the harmonic mean of precision and recall, offering a balanced measure of a model's performance.
The Lung-cancer-custom-model again performs the best with an F1-score of 0.91, which suggests a good balance between precision and recall.
The Cancer-VGG Model has the lowest F1-score (0.81), indicating that it performs relatively poorly compared to the other models.

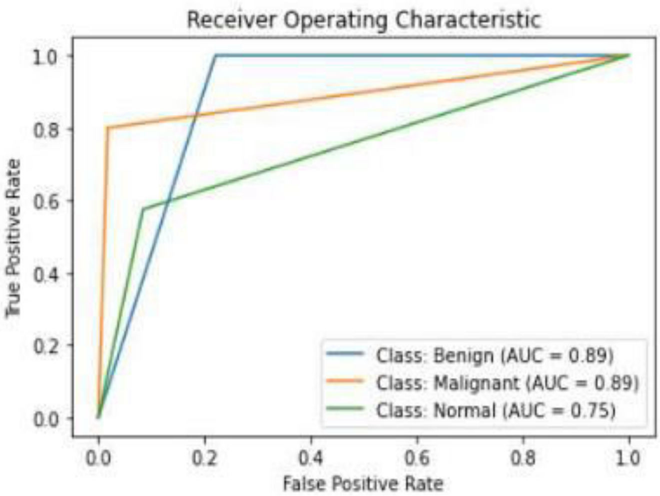

Fig.6: ROC-AUC for Lung-cancer-custom-model.

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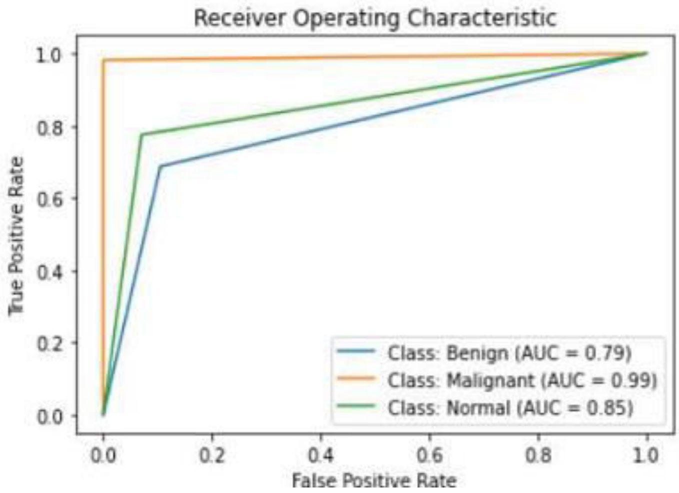

Fig.7: ROC-AUC for Lung-Cancer-ResNetModel

In Figure 7, the model achieved the highest AUC score of 89% for both benign and malignant cases, while the normal case recorded a lower AUC of 75%. This indicates that the model performs reasonably well in distinguishing between benign and malignant cases, but its performance is less accurate when identifying normal cases. In Figure 6, the AUC for malignant cases reached an impressive 99%, demonstrating the model's exceptional accuracy in classifying malignant cases. For the normal category, the model achieved an AUC of 85%, which still reflects a solid performance in accurately identifying normal cases.

Lung-cancer-custom-model consistently outperforms the other models across all metrics (precision, recall, and F1-score), making it the most efficient model in terms of both identifying positive cases and minimizing false positives.
Cancer-DenseModel and Cancer-ResNetModel perform reasonably well but are not as effective as the custom model, with slightly lower scores across the board.
Cancer-VGG Model is the weakest performer in all metrics, particularly in precision and recall, which suggests that it may not be the best option for this task.

VI. CONCLUSION

The custom CNN model has demonstrated its superiority in cancer detection within this dataset, outperforming other models in key performance indicators. It leads in identifying cancerous cases, accurately detecting 510 instances of cancer, the highest among all models. Furthermore, with only 63 False Negatives (FN), it minimizes the risk of missing cancer diagnoses, ensuring that more patients receive timely treatment. The model also exhibits the lowest False Positives (FP), with only 27 incorrect classifications, which reduces the likelihood of unnecessary treatments and reduces patient anxiety.

This model strikes an excellent balance between sensitivity (the ability to correctly identify cancerous cases) and specificity (the ability to correctly classify healthy individuals), which contributes to its high reliability and accuracy. Additionally, it achieves an impressive precision of 0.92 and recall of 0.90, showcasing its effectiveness in both identifying true positive cancer cases and minimizing errors in diagnosis. The F1-score of 0.91 further underscores the model's robust performance, reflecting a solid balance between precision and recall.

In comparison to other models, the custom CNN model consistently outperforms them in all measured metrics. Although the Cancer-DenseModel and Cancer-ResNetModel show respectable performance, neither matches the custom CNN's results. The Cancer-VGG model, on the other hand, falls short in precision, recall, and F1-score, indicating it is less effective for this task. Overall, the custom CNN model proves to be the most reliable and efficient choice for tumor detection in this dataset, making it the optimal model for this analysis.

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