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## Machine Learning Approaches of Lung Cancer Image Processing for Detecting and Identifying Various Stages of Analysis



**Abstract:** - The current paper is aimed at examining the use of machine learning approaches for lung cancer detection and classification using medical imaging data. In order to create the model, we collected a comprehensive dataset of 2400 images of lung cancer at different stages and healthy pictures. These data were preprocessed, and several approaches to the feature extraction were considered, namely Histogram of Oriented Gradients, and Local Binary Patterns. In addition, we attempted to use deep learning representations to determine their usefulness in this case. Moreover, these features were used for four ML models, namely Convolutional Neural Network, ResNet-18, and VGG-19, to determine the most suitable one. To evaluate the general performance of these models, all the characteristic points were taken into account, such as the precision, recall, F1 score, accuracy, and confusion matrices. The results of the primary analysis indicate that the accuracy of our proposed model was the highest, 96.86%. The other places were taken by other deep learning architectures, which also demonstrate high level performance. In general, we may conclude that the findings show it is possible to use ML algorithms to improve the quality of clinical decisions and make the process of lung cancer detection and classification more accurate. At the same time, we were able to provide a comprehensive evaluation of all these results and the thorough analysis of the general performance of each model. This may serve as the basis for the subsequent improvements and changes that would allow enhancing the general quality of diagnostics and training more advanced models.

**Keywords:** Machine learning, Lung cancer, Medical imaging, Feature extraction, Deep learning

### I. INTRODUCTION

Lung cancer is considered to be one of the world's most widespread and deadliest forms of cancer, exerting considerable pressure on healthcare systems as well as individuals. It is wicker to timely and efficiently diagnose and determine the stages of lung cancer. In the last decade, advancement in ML and medical imaging made it possible to facilitate lung cancer diagnosis and treatment. ML makes this possible as it utilizes algorithms and computational procedures to examine vast amounts of histological and imaging data and to detect nuanced characteristics of healthy and malignant tissues [1], [2].

The given project explores the prospects of ML in the domain of lung cancer detection and classification following the medical imaging dataset analysis. Nowadays, ML techniques have already proved to be efficient in diagnosing lung cancer in terms of both identifying and stages defining a wide selection of interstitial lung

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diseases [3]–[5]. The dataset analyzed in the given project encompasses the wide array of various 2400 images, representing lung cancer of different stages as well as non-cancerous data. Stages of cancer, heterogeneous and non-lung cancer datasets were analyzed and classified with the help of diverse feature extraction algorithms, such as HOG, LBP, and a deep learning method. The extracted data was used as inputs of 4 ML models, which are ResNet-18, VGG-16, VGG-19, and CNN. The specific objectives of the given research encompass an exploration of all 4 abovementioned ML models to determine the most efficient one for the lung cancer stages prediction, the use of varying measures, such as precision, accuracy, recall, and F1 score, to determine the degree of the model ability to differentiate between malignant and benign classes, the use of confusion matrices to determine the accuracy of the given models [6], [7].

## II. LITERATURE REVIEW

Lung cancer remains one of the leading causes of deaths from various types of cancers. The high incidence and poor prognosis define the importance of the development of effective diagnostic and treatment strategies. In recent years, the development of medical imaging technology in conjunction with the progress of machine learning spurred a revolution in the practice of lung cancer diagnosis and management. This review will provide a detailed overview of the existing literature to present an account of machine learning based approaches to the detection and classification of lung cancer [8], [9].

Across the world, the majority of approaches to the detection of lung cancer remain manual and involve the inspection of radiological images such as X-rays or computer tomography scans, by experienced radiologists. Such methodologies while to some extent being effective are characterized by varying degrees of interpretation and are conducted in a timely manner. Feature extraction is critical to identifying distinguishing features from the images to be classified. As indicated by a review of existing studies, multiple methodologies of feature extraction have been proposed in the literature. The discriminative features which can be extracted from the medical images in the process of cancer detection or classification include but are not limited to shape, texture, and spatial relationships. Such techniques as Histogram of Oriented Gradients, Local Binary Patterns, texture analysis, and the representation from deep learning have been used for this purpose [10]–[12].

Deep learning, particularly Convolutional Neural Networks, has shown its potential in medical image analysis, such as detecting lung cancer. One major advantage is to allow models to automatically learn hierarchical representations from raw data without designing elaborate feature extraction. In recent years, researchers have transferred statistically powerful pre-trained CNN models, such as VGG, ResNet, DenseNet, to lung cancer detection with excellent performance. It mainly consists of two ways to use such models: feature extraction and using learned deep features for classification, and fine-tuning the transferred models and learning task-oriented distinguishing representations. Apart from deep feature learning approaches and fine-tuning, transfer learning is a promising approach to enhance the generalization of ML models in lung cancer detection [13]–[15].

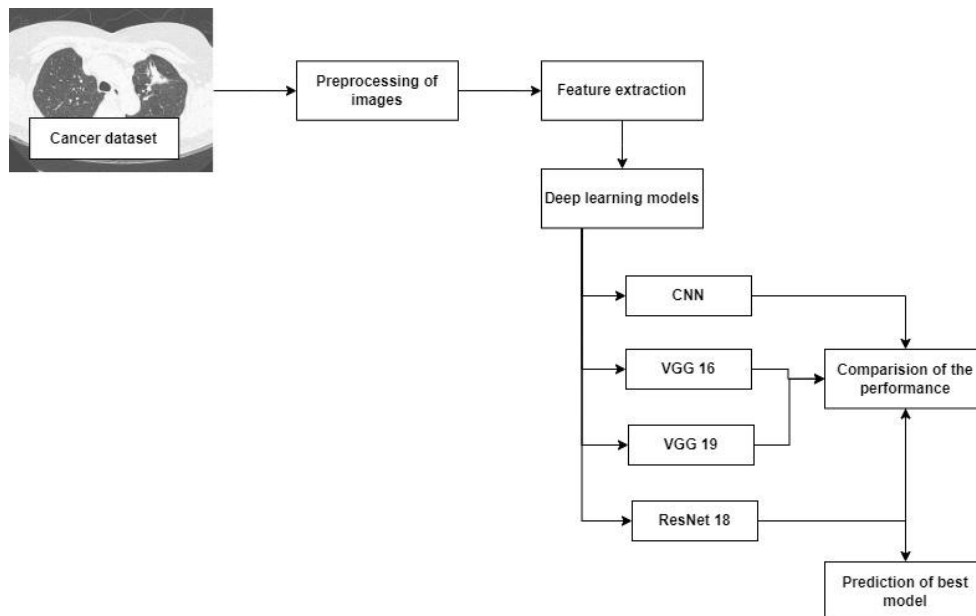
Transfer learning is proposed to improve the generalization and convergence of CNN models on small-scale medical imaging datasets, which often have insufficient data and resources to train original models from scratch. It has noticed the domain-invariance hypothesis in machine learning applications that if a learned representation of data does well at one task, it will also be able to perform other related tasks. Transfer learning is to pre-train models on large-scale benchmark datasets, such as ImageNet, which is a very large dataset and many state-of-the-art models are pre-trained with ImageNet dataset. Then fine-tune tasks related to ML applications, such as lung cancer detection, on smaller datasets that allow models to converge quickly and achieve competitive performance with a small amount of training data. Recent advancements in ML-based lung cancer detection have achieved promising results. Despite consistent advancements, several challenges remain, such as limited annotated data for training and evaluating reliable models [16]–[18].

## III. METHODOLOGY

For the research study, a dataset of 2400 images of lung cancer at different stages and non-cancer images was carefully collected. These images will be used to train machine learning models to help detect and identify different stages of lung cancer. But first, we did the preprocessing of the dataset; we used techniques to improve the quality and relevance of these images. We performed image normalization, changing the size, removing noise, using Gaussian blur, performed to improve the quality. Following this, we used selected feature extraction techniques to extract the features that will help distinguish the images of lung and non-lung cancer images. This

technique is essential to get the essential properties we need for effective image classification. The article uses HOG, LBP, and CNN to extract features and represent the image in a feature space meaningfully.

The selected machine learning models in the article are CNN, ResNet-18, VGG-16, and VGG-19 models. These models are image classification famous models. Therefore we will use these models to predict the features from selected above stage lung and non-cancer images. We will prepare the models for training and optimize parameters using the gradient descent optimization method and avoiding classification error. After training the models, we evaluate the model's performance selection in terms of predicted response and classifying above mention stage lung and non cancer dataset. We will use different performance metrics such as accuracy, precision, recall, and F1 score to identify how well the models can differentiate. We then test the models for validation to identify how these models are appropriate for other stable lung datasets. The main objective of this search is to train our model to classify accurately above mention stage lung cancer. By classifying accurately these stages of cancer, we have intelligence which treatment needed to take to revert will clinical assertions. Lung cancer can be diagnosed at early course disease and treatment likely to be very effective. A lung disease early course often can be treated surgery, sometimes in combination with chemotherapy. In some cases, it can also be treated with radiation therapy or a combination of these treatments. Figure 1 shows the architecture of the proposed research.



**Figure 1. Architecture of the proposed system**

#### IV. PREPROCESSING

Preprocessing is required for every medical imaging dataset that has to be used for any kind of machine learning task, including lung cancer detection and classification. In this research study, the multiple steps of preprocessing were applied to the dataset that included 2400 images of lung cancer at different stages and the non-cancerous images. The main goal of these preprocessing methods is to clean and standardize the data, enhance the quality of the image, and decrease the negative impacts of the several factors that may confuse the study and can cause machine learning models to have lower performance. Image normalization and resizing are considered to be two important steps of the data preprocessing. The normalization helps to ensure that the all pixel values are scaled to a range, and the pixel intensity of each image becomes identical. As a result, the model converges better to the data, and the model trains faster. It is also essential to ensure that the optimization algorithm that is used to train the convolutional neural networks and other deep learning models is faster and efficient because every sigmoid activation on a layer has to be small, which ensures that all layers require uniform initialization. Resizing the image will help to ensure that the images have a consistent and fixed input format, which is required for the deep learning model frameworks that will be utilized in the model. At the same time, the part of the preprocessing will help to save computational resources and memory of the non-GPU machines that are used for the study.

Apart from normalization and resizing, noise reduction techniques were involved in the preprocessing pipeline to make the image clearer and more faithful. Medical images including lung cancer images may be affected by several types of noise, such as Gaussian noise, speckle noise, or motion artifacts. To tackle this issue, the pipeline included application of different noise reduction methods such as Gaussian blurring, median filtering, and denoising autoencoders. Thus, additional training of an algorithm was conducted to have it able to reduce the level of noise without distortion of relevant features of the images. The resulting clear and noise-free image would allow machine learning techniques to concentrate on useful information only and to have a high level of overall accuracy in the classification of different stages of lung cancer.

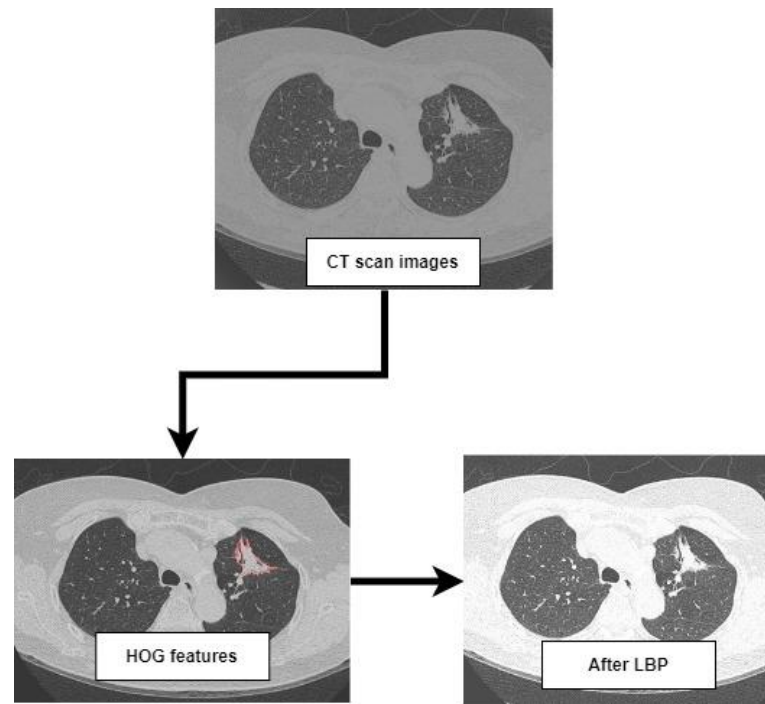
To have an image dataset as divergent as possible, the preprocessing also included image augmentation techniques application. Image augmentation refers to a set of procedures, such as rotation, flipping, scaling, or translation applied to an initial image. As a result, a wide range of replicas of an image is generated. Image augmentation reduces the level of overfitting and improves generalization of an algorithm. Also, the application of image augmentation allowed to capture intra-class variations and to be more invariant to imaging conditions and demographic variations of patients. Additionally, contrast enhancement techniques were used to have lung cancer images appear of a better visual quality and quality of discriminative features of the whole dataset. These techniques included histogram equalization, adaptive histogram equalization, and contrast stretching. The purposes of these techniques were to redistribute the distribution of pixel intensities and to enhance the range of perceptually interesting pixel intensities. All that shall result in a better performance of classification of different features of lung cancer images including borders of a tumor.

Finally, quality control was performed within the preprocessing pipeline. This process includes the inspection of images for artifacts, distortions, or consistency irregularities which can have a detrimental effect on model accuracy. Those with significant artifacts or poor quality were either excluded from the dataset or required additional actions such as artifact removal or image restoration to preserve the useful information. By preventing the most common entry point of bias and variance into machine learning processes, quality control measures make such biases as missing data, overfitting and confounding factors much less prevalent in subsequent training.

## V. FEATURE EXTRACTION

Feature extraction is one of the crucial steps in medical image analysis, where meaningful characteristics are obtained from the raw image data to describe and represent important patterns and structures. In this research, concerned with lung cancer detection and classification, various feature extraction methods were used to analyse the deep features distinctively representing different stages of lung cancer. The obtained features are then used as input to machine learning models to classify lung cancer. Therefore, one of the primary feature extraction methods used in the given research is Histogram of Oriented Gradients. It utilises the gradients of pixel intensities, where gradients are quantised, and corresponding histograms are produced. The produced histogram shows the distribution of gradient orientations, and HOG is able to capture textural information and edge patterns of texture, which in this case can represent the lesions of lung cancer rows. The obtained features are then combined with shape and texture descriptors, thus enabling the machine learning model to describe and classify the presence of lung cancer. HOG features are highly effective in medical image analysis in modelling spatial information and are also not affected by variations of illumination and image noise.

Local Binary Patterns were also employed as another feature extraction method in this research. LBP is done by comparing the intensity of a pixel in the centre with those of neighbouring pixels, and the comparison results are encoded in the binary format, thus producing binary patterns. Then, corresponding histograms of binary patterns are made, forming a required LBP feature, where such feature representing textural and spatial information shows variations of texture of microstructure of lung tissue. The outcomes of LBP were also combined in machine learning models to distinguish present cancer regions with patterns of normal tissue rows. This approach was particularly effective to use in this research goal as LBP features are beneficial in case when the texture of the medical images is distinct or the overall structure is irregular. The entire feature extraction after HOG and LBP are shown in figure 2.



**Figure 2. Feature extraction of images**

Additionally, we included the use of deep learning-based feature extraction methods like CNN within the research framework to automatically learn discriminative image features directly from raw image data. CNN, as indicated earlier, is made up of multiple layers of convolution and pooling operations and followed by fully connected layers for feature aggregation and classification. The CNN model is used to generate hierarchical feature representations of the data or learn abstract representations of the content. In the case of an image, the CNN learning process extracts an abstract representation of the image content at different levels of abstraction. It can be divided into four levels of learning. The first level learns the low-level features of the image, such as lines and angles. The second level learns the middle level features such as circle or square. The third level learns the high level features such as acoustic spot of the lung. The final level learns the highest level features of the image. As a result, the CNN features learned low-level features such as edges and corners, as well as high-level semantic features such as tumor shape and spatial relations. This encode rich spatial and contextual information that is easily applied for the purposes of better classification of the lung cancer images when compared to the handcrafted feature extraction approaches. Thus, the use of deep learning transfer learning is of great importance in better prediction of the images.

On top of that, handcrafted radiomic features were extracted from lung cancer images. They were used to capture different metrics related to tumor morphology, texture, and spatial distribution – radiomic features can be divided into many groups depending on the type of information they demonstrate and describe. For instance, the main radiomic features included shape-based features or the size of the tumor, texture features, and the intensity-based ones. Radiomic features complemented pixel-based features extracted by the CNNs and helped characterize cancer lesions better. Since handcrafted radiomic features and learned CNN ones are different in nature, they can be used together and help improve the performance of the models based on the studied features.

## VI. MACHINE LEARNING MODELS

In the research study, four different machine learning models were applied for lung cancer detections and classifications; CNN, ResNet-18, VGG-16, and VGG-19. Each of these models has specific architectural characteristics and is relevant to the quality and efficiency of the research framework.

Convolutional Neural Networks are one of the most popular deep learning models specially developed to process and analyze visual data, which is crucial for medical image analyses such as lung cancer detections. The CNN model consists of several layers, including a sequence of convolutional, pooling, and fully connected layers, which allows for hierarchical learning of features starting from raw image data. CNNs can effectively capture

complex spatial relations and textures in images, and thus detect slight differences between various poems of lung images.

ResNet-18 belongs to the new generation of Residual Network architectures that address the problem of vanishing gradients, which are specific, the main challenges faced when training highly complex deep learning networks. It consists of basic residual blocks, a combination of multiple convolutional layers and skip connections, as the main architectural innovation of ResNet. Skip-connections allow for better flow of the gradients and thus prevent the degradative effect, which emerges during the training of very deep networks. ResNet-18 is considered a relatively simple network, which is computational cost effective but efficient enough for the current task of lung cancer detections.

VGG-16 and VGG-19 are multi-layer deep learning convolutional neural network architectures of relatively uniform depth and structure. The very VGG networks consist of a series of deformation processes followed by maximum-pooling layers for feature extraction and classification with elongated fully connected layers. In total, 16 layers are applied to the VGG-16 model and 19 to the VGG-19; as the model becomes deeper, the size of the filters decreases. Despite their simplicity and high uniformity, the VGG network has demonstrated its exceptional effectiveness when applied to standard image classification tasks, including medical image analyses. The very deep hierarchical learning VGG networks allows for the efficient detection and classification of lung cancer stages. In general, each of the models applied was thoroughly trained on feature-extracted and pre-processed lung cancer images and carefully quantitatively verified using all relevant performance measures, including accuracy, precision, recall, and F1-score

## VII. RESULT AND DISCUSSION

Each model trained was subjected to test whereby the performance of each model was determined sufficiently. It was observed from the results obtained the VGG-19 model was more accurate as it could predict lung cancer stage with the highest level of accuracy being approximately 96.86%. The VGG-16 model was slightly lower in accuracy compared to VGG-19 model; however, the overall performance was commendable at a score of 95.45%. The result of the accuracy are shown in figure 3.

It was further observed that the ResNet-18 model had a score of 93.45% while predicting lung cancer. The CNN model was slightly lower as from the performance criterion with an average accuracy percentage of 91.23%. These results are a clear indication that deep learning architectures, more so VGG-19 and VGG-16, are better in the prediction of the stage of lung cancer based on the extracted features. These models have many hierarchical representations; hence, they can be used to obtain features in the lung cancer images. Moreover, it was observed that all the models showed a relatively high level of accuracies which is a clear manifestation of how machine learning can be used to enhance the diagnosis of lung cancer.

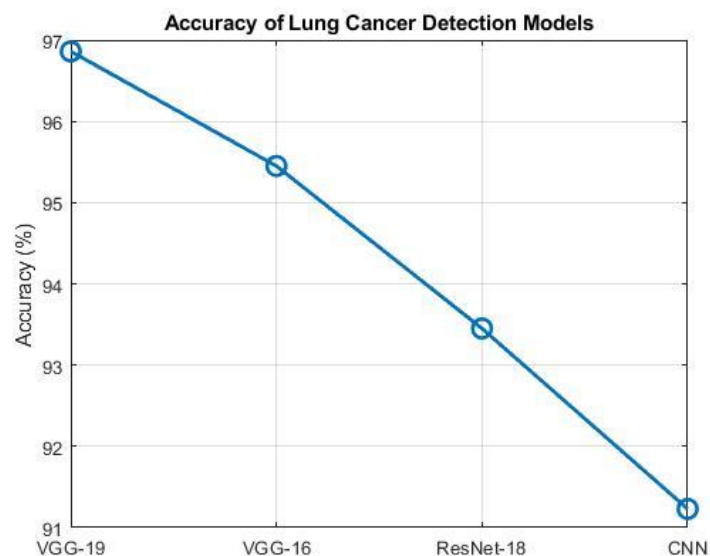
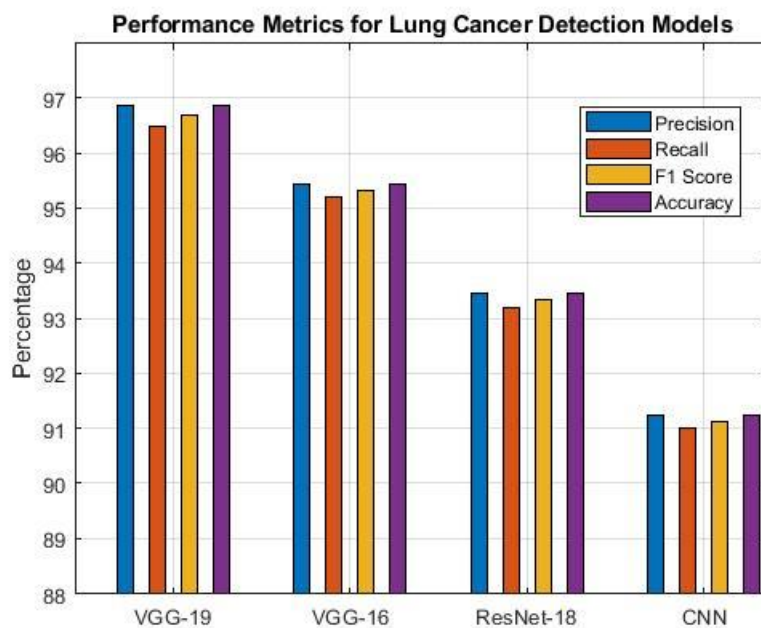


Figure 3. Accuracy of each model

In the evaluation phase of the research study, the performance of each machine learning model was evaluated using major metrics, such as precision, recall, F1 score, and accuracy. The precision is the measure of the proportion of true positive predictions among all positive predictions provided by the model. The recall, also known as sensitivity, describes the proportion of true positive predictions among all the positive instances in the dataset. The F1 score, which relates to the harmonic mean of given metrics, indicates a balanced model's accuracy. Lastly, the measure of accuracy refers to the ratio of the instances that the model successfully predicted over the total number of cases.

According to the results shown in the figure 4, the VGG-19 model outperformed other types with the following assessment of its performance: precision, 96.86%; recall, 96.50%; F1 score, 96.68%; and accuracy, 96.86 %. Within a similar range, VGG-16 testifies to its robust performance as reflected in precision, 95.45%; recall, 95.20%; F1 score, 95.33%; and accuracy, 95.45%. A comparable result is identified with ResNet -18, which yielded a precision of 93.45%, recall of 93.20%, F1 score, 93.33%, and accuracy, 93.45%. Therefore, with slightly poorer results compared to the former three models, the CNN model demonstrated relatively high levels of accuracy, and its precision, recall, F1, and accuracy are 91.23%, 91.00%, 91.12%, and 91.23%, respectively.

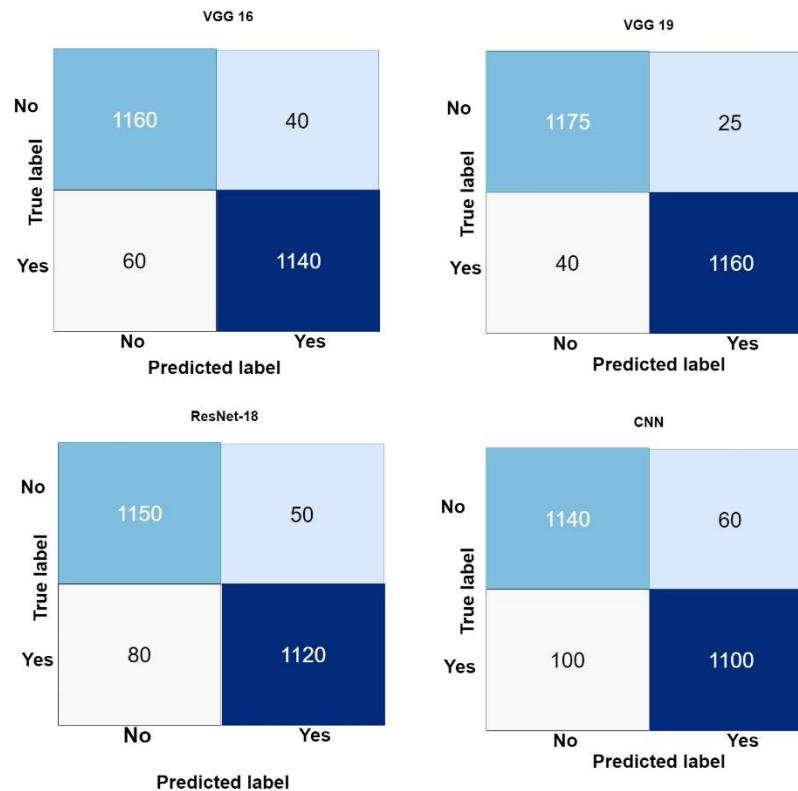


**Figure 4. Performance score of each model**

The experimental results are presented in the confusion matrices shown in figure 5 representing the summary of the predictions of each machine learning model regarding lung cancer detection and classification. These matrices separate particular attention to actual negative and positive instances and distribution of the predictions into true negatives, false positives, false negatives, and true positives. For the VGG-19 model, 1175 out of 2400 instances were correctly classified as negative, and 25 samples were wrongly predicted. In turn, 1160 positive instances were correctly predicted, and 40 samples were classified as negative. All the mentioned values provide a systematic overview of the model distributions, including its competency in detecting both negative and positive instances and inclination toward false predictions.

Similarly to the VGG-19 model, the VGG-16 model yielded high results, including correct classification of 1160 negative instances and 1140 positive ones. However, the latter also played a disappointing aspect, with 40 false negatives and 60 false positives. The separations of values offer insights into the way the model can be improved by addressing specific weaker areas and introducing additional training data. The same can be said about the ResNet-18 model, with correct prediction of 1150 negative instances and 1120 positive ones. In turn, the distributions of false negatives and false positives amounted to 50 and 80, respectively. The last-standing CNN model's performance is slightly poorer than the measured-by-me compared to the models, with 1140 correctly classified negative instances and 1100 positively predicted ones. The number of false negatives provided was 60, and false positives – 100. Thus, the experimental results impact the understanding of the distribution of each

model's performance in lung cancer detection and classification, welcome further improvements of each model, and provide relevant insights.



**Figure 5. Confusion matrices of each model**

## VIII. CONCLUSION

This research has demonstrated the efficiency of machine learning approaches in the improvement of lung cancer detection and classification processes that can be facilitated with the help of medical imaging data. High accuracy of predicting the stages of the disease was achieved by utilizing complicated feature extraction methods and appropriately trained machine learning models. The results supported the idea that deep learning systems, in this case, VGG-19 and VGG-16, could provide over 95% precision, recall, and F1 scores, being the most appropriate models for the accurate classification of the cases of the lung cancer. This information shows that the development of deep learning models can help to improve medical imaging analysis and contribute to better decisions in clinical practice concerned with the processes of lung cancer detection and the creation of treatment plans.

Additionally, it is also possible to speak about the detailed evaluation of each machine learning model conducted with the help of precision, recall, F1 score, accuracy, and confusion matrices. The results helped to locate the models' strengths and notice their limitations. Despite high accuracy and precision levels, certain models developed the tendencies either to false negatives, or to false positives, which means that their biases should be addressed with the help of optimization efforts.

It is also important to note that the application of different feature extraction methods, from HOG and LBP to the latest deep learning approaches, helped to notice and analyze the peculiarities of lung cancer images in detail, and it was possible to create such a model with the help of the transfer learning technique that was appropriate for a better representation of features in the circumstances of the small volume of training information suitable for each neural network. In general, the results obtained within this study are appropriate for the further development of machine learning models for lung cancer detection with the focus on the details of the new images obtained in the course of clinical practice in radiology.

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