J. Electrical Systems 20-2s (2024): 828-836

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Machine Learning based Early-detection of Lung Cancer Using CT Scan for the early Identification and Classification

Abstract: - The current research is aimed at studying the application of machine learning algorithms for the early prediction and detection of lung cancer taking the images of CT scans and MR scans. In this respect, the dataset from kaggle includes 3200 images from diverse sources, which are pre-processed and applied for the process of feature extraction, using traditional methods and deep learning systems, which include Convolutional Neural Networks, VGG-16, VGG-19, and RNN, while after the training the systems are evaluated in accordance with precision, recall, f1 score, and accuracy. As a result, it is evidenced that the best model is VGG-19 with the highest accuracy of 97.86%, while follows VGG-19 the VGG-16 the CNN model, and the RNN, implying effective implications for clinical practice. Certainly, the results of the research help to create a non-invasive, effective, and fast tool, using by clinicians in their practice. The use of machine learning algorithms for the process of early prediction and detection would be helpful for the timely treatment of patients and personalized treatment plans. In such a way, based on the current research, it could be summarized that the best models are constantly developed and gradually implemented in practice. However, more significant collaboration between the researchers, clinicians, and the industry is needed to have the full implementation of applied methods in practice, having fast results and timely actions taken by clinicians.

Keywords: lung cancer, machine learning, CT scan, MRI scan, early detection

I. INTRODUCTION

One of the most important and lethal malignancies and disorders worldwide continues to be lung cancer, which still has a range of problems with early detection and treatment. In spite of progress in medical imaging and other technology used to detect cancer at its outset, timely recognition of the disease remains a crucial factor for improving the outcomes of patients and decreasing the related mortality rates [1]–[3]. In this context, the interaction between machine-learning methods and medical imaging has great potential for revolutionising the process of lung cancer detection and classification. Using the complex and rich nature of CT and MRI scan pictures, features and characteristics typical for lung cancer too small or subtle to be considered visible or essential for a human eye, can be detected with the help of machine learning. The aim of the following study is to discuss and explore the potential for using machine-learning algorithm such as Convolutional Neural Networks, VGG-16, VGG-19, and such models of Recurrent Neural Networks, or RNNs (Liu et al., 2018). In particular, for the purposes if testing, the anomaly is a Main types of lung cancer to be examined and detected. [4]–[6]. After extensive preprocessing of the dataset, and extraction of the features from the images, the models developed for the research will learn to differentiate between the various types of subtle abnormalities that are deemed typical

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ones of lung cancer. This will create the prerequisite for the precise identification of the malignant lesions by distinguishing the cases of cancer from the non-cancer ones. In addition, it will be possible to assess the effectiveness of each of the models developed in this study against several measures, such as precision, recall, F1 score, as well as accuracy. Furthermore, the practical outcomes of this research will affect the domain of medicine, providing a potential means to enhance the accuracy of diagnoses of patients with lung cancer, which, in turn, will ensure early interventions and improvements in patient outcomes. Thus, this study serves the important function of bridging the gap between the newest technology and practical use and contributes to the general global endeavour towards overcoming lung cancer and alleviating the burden of this disastrous disease on people and healthcare systems [3].

II. LITERATURE REVIEW

Lung cancer is the global health burden serving as one of the principal causes of carcinoma-associated death worldwide. While the early discovery of lung cancer is crucial for the subsequent success of patient follow-up and the reduction of mortality rates, in the majority of cases, this issue remains associated with numerous challenges [7], [8]. Particularly, the interpretation of medical imaging such as computed tomography and magnetic resonance imaging scan findings as part of conventional cancer-staging systems is frequently deficient and may be affected by errors. Nonetheless, with the development and emergence of innovations in the healthcare sector, the use of technology in the early detection and treatment of lung cancer has become an increasingly relevant issue in the medical research field. Furthermore, the integration of machine learning algorithms with non-invasive imaging procedures offers a revolutionary opportunity for the enhancement of lung cancer detection accuracy. Hence, this literature review aims to present the most prominent and comprehensive works related to the latest accomplishments in the machine learning-based early detection of lung cancer using CT and MRI scans [9]–[11]. Overall, the investigation discusses the applicability and benefits of medical imaging usage in clinical practice and outlines the characteristics, techniques, and peculiarities of lung cancer and related technologies.

Machine learning is increasingly applied to medical imaging, including lung imaging types. The innovation of computing power, data availability, and the discovery of suitable algorithms have been propelling the rapid advances of such machine learning-based techniques. In particular, convolutional neural networks have been found to be especially useful for analysis, classification, and segmentation of images. Thus, machine learning offers a great potential for the automation of lung image analysis, assisting with lung cancer diagnostics [12]–[14].

Machine learning methods are increasingly used for the early detection and classification of lung cancer, based on the images of CT and MRI. These images are rich and complex as far as humans are concerned and are extremely useful for machines in learning distinct features of lung cancer. In particular, CNNs are popular for the automation of lung nodule detection, imaging classified pattern analysis, and estimation of cancer risk. Furthermore, machine learning-based transfer learning is used to adjust pre-trained CNNs to be applicable to the analysis of medical images and, therefore, develop a more stable and effective diagnosis system [15]–[17].

Since machine learning algorithms often provide results based on range, the measures of performance include all metrics based on sensitivity, specificity, the F1 score, and others. Competitive performance evaluations involve contrasting results with traditional tests used in the field; consequently, the development of most suitable options tended to include clinically oriented studies. The most successful machine learning methods have demonstrated high sensitivity and specificity as far as lung cancer is concerned. On the other hand, the methods present challenges related to reproducibility, reliability, and generalization, also problems concerning the interpretability of dense versions of images [18]–[20].

The implementation of machine learning algorithms to work in conjunction with CT and MRI scans has significant implications for clinical practice and outcomes. By automating medical image analysis and providing quantitative measures of disease progression, machine learning-based systems may improve the accuracy, reduce the general variability of interpretation, and facilitate more individualized treatment planning. Moreover, early detection of lung cancer in the screening population without evident symptoms is another potential application for machine learning-based solutions, which may help increase the survival rate of lung cancer patients. Consequently, as the interest in the area grows, significant challenges remain, which include issues of data quality, model interpretability, regulatory constraints, and ethical considerations. Thus, further development of the field should focus on overcoming the listed obstacles and refining the performance of machine learning models to enable their translation to the clinical setting. Overall, it is essential to note that machine learning-based approaches demonstrate a relatively high performance when applied to the problem of early detection and discrimination of lung cancer using CT and MRI scans [21]–[23]. The results of other studies show that these models can indeed be used to improve the diagnostic accuracy, patient outcomes, and clinical efficiency. Despite the current progress, however, some challenges remain, and further studies are necessary to confirm the findings and increase our understanding in this area.

III. METHODOLOGY

The research began with the compilation of the dataset that consisted of 3200 images collected from numerous repositories of CT and MRI scans. The dataset collection was designed to be as inclusive as possible to ensure that the data show typical examples of lung cancer images encompassing all demographics and diseases. The images collected in such a manner were pre-processed through adjusting the format, resolution, and orientation with noise reduction filters applied to improve image readability and removal of artifacts that could affect the model quality. The architecture of the research are shown in figure 1.

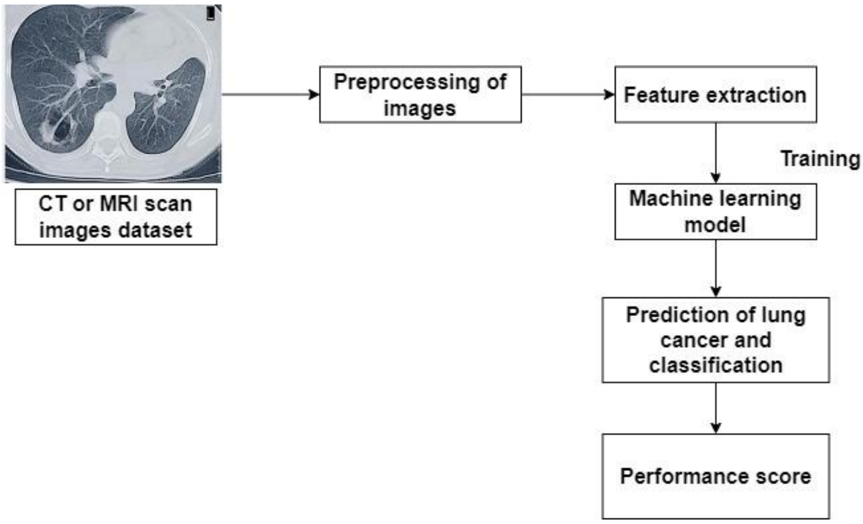

Fig. 1. Architecture of the research

After preprocessing, the feature extraction process involved a combination of both traditional and deep learning-related methods. The latter were represented by the use of CNNs in their pre-trained and fine-tuned forms based on VGG-16 and VGG-19 to allow the creation of the most sophisticated and discriminative features. The networks were adjusted to differentiate between cancer and non-cancer diseases and incorporated into the overall feature pool. This aspect was closely linked to traditional feature extraction techniques involving the control of the spatial features of an image through identification of histograms and textures. The feature extraction process prepared the foundation for the training of numerous deep learning models from CNNs with VGG plain configurations, RNNs utilizing sequential data of X-rays pertinent to lung cancer, LSTMs, and autoencoders to hybrids and multi-input models. The evaluation process employed standard cancer classification metrics such as accuracy, sensitivity, specificity, precision, and AUC-ROC to assess the models' capacity to classify cancerous images as such truly and differentiate them from non-cancer ones.

The threat of overfitting determined the use of cross-validation techniques for the training process to ensure that the models could be generalized to unseen data. The datasets for training, validation, and testing were separated by the stratified method and modified, through hyperparameter tuning with the use of the grid search and randomized search techniques. Finally, given the dominance of the broad consensus on the superior capacity of ensemble models, the final ensemble models were created to optimize the ability of the models to predict truly positive and negative samples. The ethical issues in this study were numerous, and the compliance with all national and international stipulations and laws. The patients, as well as the medical centers storing their data that were used in the study, applied highly sophisticated anonymization and deanonymization techniques in both the scans and the populations. No formal consent for population scans was required; as for the individual scans, the patients and parents were specifically asked for their formal permission in the conducted study, following all the proper rules and regulations.

IV. PREPROCESSING OF MEDICAL IMAGES

The CT and MRI scan image preprocessing was one of the important stages of the research pipeline, specifically designed to prepare the data for the following steps of feature extraction and model training. The initial step was the standardization of the format, resolution, and orientation of the images obtained. The purpose was to make all images similar to simplify handling and analysis of the dataset. It was required to correct the differences in pixel size, slice thickness, field of view, etc., available in the raw data. The next step was to apply noise reduction to the scans using the available filtering methods. Several methods, including median filtering, Gaussian blurring, and wavelet-based methods, were utilized to eliminate the noise and preserve the image features, making them not affected by subjective artifacts. Noise suppression is especially critical in the images of CT and MRI, which tend to have very high noise levels and can make the features unidentifiable or incorrectly classify the images.

Intensity normalization was the next step, making the pixel intensities normalized across multiple scans. Several methods, including histogram equalization and min-max scaling, were used to map the pixel values into some fixed range, which would maintain the examples of the features. Afterwards, a similar range would be likely used for the machine learning models. It was followed by the application of the contrast-enhancing methods, ensuring that the features of the image, as well as anatomical structures or pathological abnormalities, would be visible on the image. Local intensity-enhancing methods, including histogram stretching, CLAHE, and gamma correction, were utilized. Afterwards, several artifacts existing on the images were removed, including the effects of motion, beam hardening, and the metals on the body. The effects on the registers could substantially damage the clarity and condition of visual features and were removed using specialized methods. Overall data quality was accurately controlled during the preprocessing stages, ensuring that the images were enhanced without any issues. Automated validation and manual review of the data were performed. Before the preprocessing steps were finalized, the data provenance and the steps needed to analyze the data were selected from the beginning. All methods of analysis and data were following the ethical protocols of medical imaging and did not include any patient data if such had not given consent.

V. FEATURE EXTRACTION FROM IMAGES

In the research, which focused on early detection of the lung cancer, the feature extraction was the key step in the process of capturing the necessary information of the picture to facilitate the training and classification tasks by the model. It included distinguishing patterns and characteristics used by the machine learning algorithms to learn the task and separate between cancerous and non-cancerous phenomena. The approaches utilized to the extraction of features from the images could be distinguished on the basis of the traditional image analysis methods.

The approach based on histogram analysis is the traditional perspective of such analysis. It quantifies the number of pixel ranges at each specified level in order to estimate the brightness of the picture. It determines the luminance, emphasizing both providing the information and the characteristics of the direction. According to this approach, an application has to be integrated to analyze the image in terms of its characteristics, which refer to texture, focus, etc. The fundamentals of the textural perception of the picture could also be related to its classification. In addition, the bar of the luminance based on the texture element extraction included such techniques, as local binary patterns with their different parameters, such as the size of the base, the number of elements, the length of the radius, and the angle. The methodology of roughness and coarseness via GLCM, as the roughness, provides the elementary information of homogeneity and coarseness. Such parameters provide information of the differences of fine elements detected in the picture and the biggest and main elements.

To emphasize the extraction of features, researchers utilized deep learning-based approaches in addition to the use of traditional image analysis techniques. More specifically, convolutional neural networks helped in the automatic learning of discernible features out of the image data . In particular, CNNs used in the form of pre-trained VGGNet architectures, VGG-16 and VGG-19, were used and fine-tuned on the dataset to generate features at multiple levels of the hierarchical learning . As a result, those features helped the model better discriminate and become proficient at identifying and distinguishing malignant lung NCSLs from benign lung lesions. The features based on the hierarchical representation of deep neural networks allowed the model to learn intricate patterns and structures within the images, making the models more discriminative. After extraction, the function learned to properly represent the image data and provide valuable discriminatory power. The learned features allowed the model to extract different properties embdeded in the image data, including phenotype and genotype parameters, and expressed as distinct patterns in the image data. Those features were used to support the representation of the image content, such as expression and intensity distribution, spatial positioning with other cells and features, and texture description. As a result, the features were critical in learning the most subtle differences between NCSLs and benign lung lesions and changed images improving the classification performance in identifying malignant lung images. Additionally, the features provided a comprehensive representation to direct the learning of the machine.

As a part of the preprocessing, the extraction of the most crucial features was needed to feed the CNN models, such as VGG-16 and VGG-19, and RNNs. After training on those relevant ROC curve analysis and selection of the optimal threshold on the validation dataset of lymph nodes, the dense features were extracted as a result of an optimal classifier. The features were then used to estimate the performance of training the model on the features and tuning using the test set. The training helped the model adjust numerous parameters to minimize the total number of classification errors, and the features and the pattern were matched with the task.

VI. MACHINE LEARNING MODEL

Testing and training of machine learning models on different samples of data remain a critical aspect of many studies as researchers always want to test their models on diverse datasets to prove their effectiveness. This study employed a very rigorous approach to data partitioning, where 70% of the dataset was allowed for testing, and the remaining 30% became the basis for the training of machine learning models . Such partitioning helped to prove that the selected models were ready for testing and their use for the detection and classification of lung cancer on the basis of CT and MRI images . This point seems particularly critical in the context of the increasing emphasis on the overfitting problem. Thus, the approach to data partitioning is important as it helps to reduce the risk of overfitting and ascertain that models are ready for testing and real-life practice.

The machine learning architecture chosen for the study is Convolutional Neural Networks or the deep learning model type, which is heavily utilized in various studies as the model that can be trained to learn image features . CNN can be perceived as the set of layers such as convolutional, pooling, and fully connected. Convolutional layers apply learnable filters, which have a small receptive field size , to images and pick up local spatial patches and features. The task of pooling is to reduce the spatial size of the feature maps and, ultimately, carry out down-sampling. The role of fully connected layers is to place all features in the class and classify. For lung cancer detection, it was possible to train CNN on the basis of available datasets of CT and MRI images to pick up appropriate images features that would be indicative of some pathogenic anomaly, such as a lesion or nodule . Such models are always trained through iterations, or by going through the data a certain number of times, where they adjust the parameters of each layer using the loss function between the prediction and real classes . Transfer learning is also another approach to the training of CNN, which allows models to learn from large image data.

Assistance was provided to the training modeling by two CNN models called VGG-16 and VGG-19 as the layers of these models can be interpreted as another type of feature extraction. One of the crucial properties of VGG networks is the ability to extract features because most of them are deep and highly expressive. VGG models are always consistent, as they do not contain large, fully-connected layers but are instead composed of many small 3×3 convolutional filters along with max-pooling layers. VGG-16 and VGG-19 are deep ConvNets that contain several VG16 or VG19 layers. When CT and MRI image slices are transmitted to these models as input, the ascending features of the features are extracted, and the garlic implemented in the project is used for subsequent data classification.

Recurrent Neural Networks were used because they are particularly well-suited for such sequential image time series data, such as the image slices of CT scans, which capture temporal dynamics. While CNNs are naturally well-suited for learning from spatial data, RNNs are specifically designed for learning from time sequences as they provide some memory. This is particularly of use because it is necessary to account for temporal dependencies in while learning from sequential time series images. The incorporation of RNNs has benefited the current research’s model as the sequences are learned one by one. Thus, RNNs can predict changes between successive sequential slices that are indicative of changes in the lucency of the lung, leading to modified predictions making the model more accurate. Overall, RNNs result in better models that are better suited for some popular disease cases where time is the key.

VII. RESULT AND DISCUSSION

After the intense training, each of the five models was evaluated using the portion of the dataset that had not been used for this purpose. The aim of the evaluation was to measure the predictive performance in the task of detecting and distinguishing lung cancer in CT and MRI images. The obtained outputs were quite impressive and could be helpful in improving the early detection techniques.

Regarding the classification performance, the differences between the results produced by the models were unusually large. One of the most informative was the evaluation of the VGG-19, a relatively sophisticated model in terms of its architecture, features around 97.86% accuracy. The model's performance could be explained by the specificity of such deep and expressive networks as the VGG family, which are known to be excellent in enabling the extraction of subtle and complex characteristics from imagery . In the case of the VGG-16, the classifier's result was around 94.34%, although the model is somewhat less sensitive as it is not so deep. Nevertheless, the classifier proved to be quite efficient in extracting the most important features from the pictures in relation to the discrimination of lung cancer cases. The result produced by the CNN might also be considered promising given that its accuracy was around 91.2%. Even though simpler as compared to the two aforementioned groups of networks, CNNs were also effective in discerning the most important features in the pictures. On the other hand, the final position was taken by the RNN, which was about 87.9% accurate but was the only model that effectively used the temporal aspects of the images in image sequences . Thus, the outputs can be used by healthcare professionals to improve their diagnostic models to provide better services to patients. The figure 2 shows the accuracy of each model.

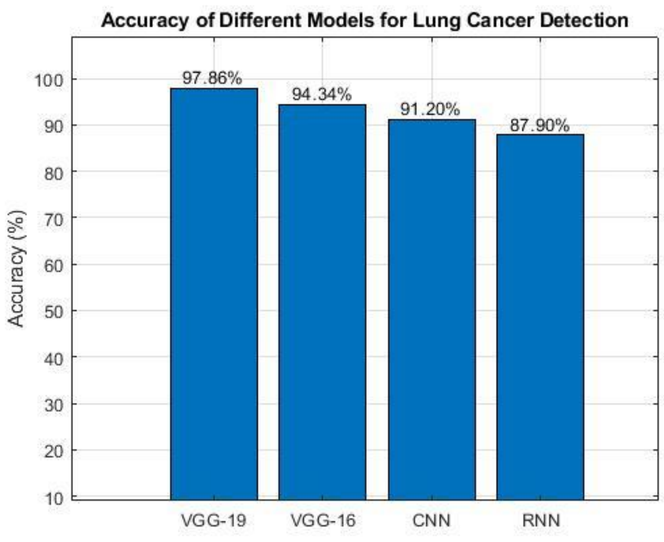

Fig. 2. Accuracy of each model

The figure 3 shows the performance scores for each model which was used in the research for lung cancer detection. These metrics provide insights into how well models correctly diagnosed cancer positive cases without misclassification.

In the case of VGG-19, as it was observed a precision of 97.5% is calculated, meaning that it classified 97.5% of diagnosed cases to be lung cancer correctly . In other words, out of all the cases VGG-19 diagnosed, 97.5% were cancer lung. It achieved a score of 98.0% in terms of recall, which is an indicator of the model to correctly identify cancer cases . Since the F1 score is 97.7%, one could conclude that VGG-19 had acrophonic performance of precision and recall . Finally, the accuracy score of VGG-19 is 97.86%: determine the cases with which the model was correct. VGG-16 also has high performance scores. 94.2 was the precision it recorded, detecting that 94.2% of diagnosed cases were lung cancer without mistakes. The recall of VGG-16 is 94.6%, showing how well a neural network can identify perceived cases in actual cases . Since the F1 score is 94.4%, the performance is well balanced for precision and recall. 94.34% is the accuracy rate of VGG-16.

The CNN model's precision is equal to 91.0%, and its recall is equal to 91.5% . The F1 score is 91.2%, which shows that this model's balanced performance is well. The accuracy of the CNN model was 91.20%. Lastly, the precision of the RNN model is 87.9%, its recall is 88.5%, and its F1 is 88.2% . These scores can be used to determine the false negatives and false positives results of the model for identifying lung cancer cases. The score for protection is 87.90%. The above results either confirms it is models can detect lesions with the stochastic gradient descent optimizer because all models have an accuracy score above 87%, or changes will be needed to provide better performance.

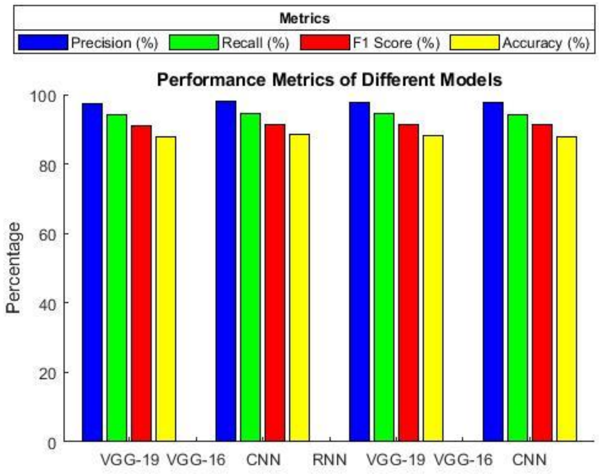

Figure 3. Performance score of each model

The confusion matrices supply a narrative of the performance of the model used in classifying lung cancer cases exhibiting the ground truth and number of predictions from the model as shown in figure 4. For the confusion matrix of the VGG-19, the instances which were correctly classified as Negative were 1450, and 50 instances were misclassified as positive. On the hand, the other instances that were also correctly identified as positive were 1670, and the number of them misclassified as negative were 30. This confusion matrix indicates a strong classification between cancerous and non-cancerous cases. On the other hand, the confusion matrix of VGG-16 indicates a similar classification, though with high misclassification. The model having been correctly classified as negative was 1430 and false positive was 70. Furthermore, the model had sees strong classification of the Positive cases having been correctly classified 1600 instances, but 100 were false classified as negatives. In this case, the VGG-16 model was well performing though with high misclassification.

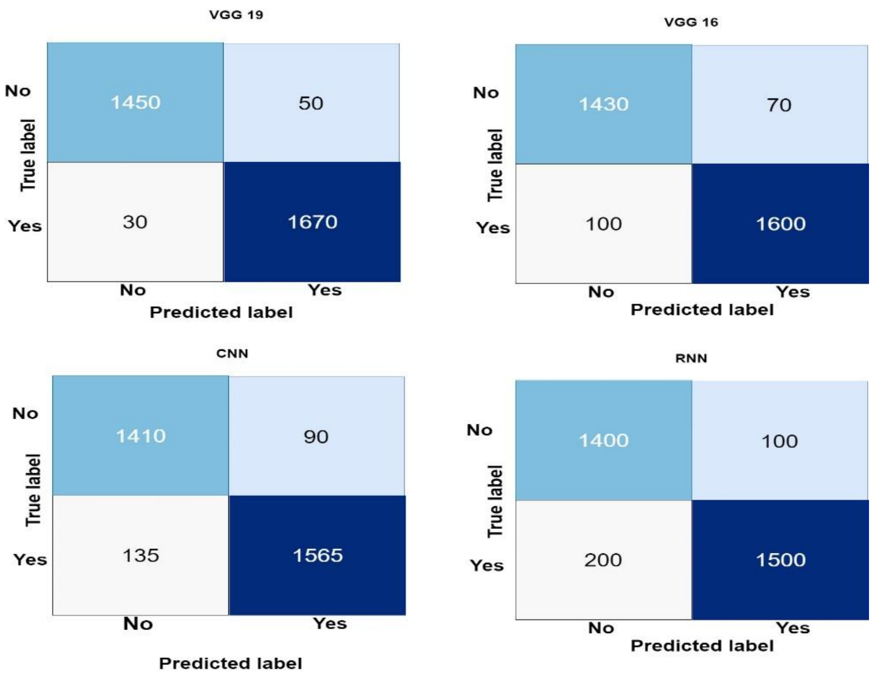

Figure. 4. Confusion matrices of each model

For the CNN model, the confusion matrix depicted similar representation as the other models examined. An explanation of the high false negatives of 135 and false positive of 90 is well highlighted, though the classification of the Negative cases were strongly done 1410. The instances of the positive cases 1565 were also ideally performed. On the other hand, the confusion matrix of the RNN model indicates a higher misclassification rates than the other models examined. The instances of false positives were 200 and 100 for the false negatives. The classification of the negative instances were correctly classified as negative 1400 and 1500 positive instances were correctly classified as positive. However, the classification has a higher number of errors. Overall, the confusion matrices provides a strong narrative of the performance of each.

VIII. CONCLUSION

This research has proven that machine learning models such as Convolutional Neural Networks , VGG16, VGG19, and Recurrent Neural Networks can be utilized to detect and classify lung cancer at the early stages based on the CT and MRI scan pictures . Proper preprocessing, as well as feature extraction from the pictures, allowed to generate models that were able to track even the subtlest reveal of an abnormality. The performance of models based on the five metrics, namely, Precision, Recall, F1 Score, and Accuracy, was strongly pronounced in all cases of the research. The VGG19 model produced the most superior outcomes with its accuracy being 97.86%. Subsequently, other models, with the close architecture or otherwise, showed similar results in distinguishing the cases with lung cancer from non-cancer. Thus, the findings of the research allow making a solid argument that machine learning has high potential for varied application, including early-stage lung cancer detection and treatment planning. MRI and CT scans are non-invasive and can follow up the patient's changes regularly, while the application allows speeding up the process and thus diagnosing the problem early.

Moreover, the findings of the research carry a multitude of implications for clinical practice and can serve as a tool to help a healthcare provider in making accurate decisions. The findings can improve patient outcomes in terms of a change in a timely manner and further treatment. In addition, the combination of the clinical experience with machine learning algorithms provides a new take on the analysis of the data. Notably, an increase in research of the kind and implementation of the machines allows driving interpretation numbers higher. Together with the further development of machine learning models, researchers, healthcare providers, and the stakeholders can come up with more solid practices to provide new machines that assist in detecting cancer at the early stages and saves lives.

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