Effective lung cancer detection using integrated ML and DL models

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Abstract
This research is about the real-world application of deep learning methods to identification of NSCLC subtypes using the CNN models. The data is constituted of CT scans of NSCLC subtypes which are adenocarcinoma, large cell carcinoma, squamous cell carcinoma and normal lung tissue. An investigation of the four CNN models—i.e. CNN, VGG16, InceptionV3, and ResNet50, is done for their role in classifying NSCLC subtypes. Of course, through special kinds of experimentation and general comparison. There are several steps in the methodology that include data preprocessing, model creation, hyperparameter tuning, and performance assessment. instances of the representation such as accuracy and loss graphs help visualize the performance of the model. The workflow stipulates the utilization of deep learning algorithms for the medical image analysis of lung cancer, which could be useful in earlier and more accurate cancer detection.
Keywords- Deep Learning, Convolutional Neural Networks, Non-Small Cell Lung Cancer, Image Classification, ResNet50, Inception V3

1. Introduction

Lung cancer still ranks among the important causes of death and cancer related ones in the global community, where non-small cell lung cancer (NSCLC), constituting more than 85% of all lung cancer diseases, remains the most frequently encountered form. Staging NSCLC and classifying the subtypes at their earliest states is extremely important to make better and apt preparations for treatment and improve outcomes of patients. Though the routine techniques of biopsy, histopathological diagnosis, and etc still are used for diagnosis, they are invasive and time-consuming. In addition, routine methods may yield the sampling errors. For this reason, non-invasive and user-friendly diagnostic kits that can assist in the early stage identification as well as division of NSCLC subtypes should be searched for.

At this point in time, deep learning, a subset of artificial intelligence which is modeled after the structure and functions of the human brain, has demonstrated an astonishing capacity to learn tasks in the field of medical image analysis. Convolutional Neural Networks (CNNs), a class of deep learning architectures, have been widely used lately in many image processing applications as they have been shown capable of acquiring representations that capture the underlying hierarchy through incoming raw data in a highly organized manner. CNNs, for example, have demonstrated the capability to deal with CT scans used for detection and classification of lung cancer.

The prior studies in the area of deep learning employed in lung cancer detection (mainly binary classification tasks) have predominantly concentrated on the distinctions between cancerous and the non-cancerous lung tissues. While these studies reveal positive outcomes, however, there is a significant illusion of the variant classification phenomenon that is paramount in the personalized treatment programs. Besides, the research that is not well founded on experts' opinions and at times the numbers of subjects involved are few yet the study is still useful.

Its our objective to address these scarcities by designing and evaluating CNN models for NSCLC diagnosis as well as subtyping. We use CT scans having images of adenocarcinoma, large cell carcinoma, squamous cell carcinoma and normal lung tissue constituting a large database. Our work advances the state of knowledge in this area, because it is centered on the classification of subtypes, which ensures that the medications are more tailored and accurate.

The main goal of the research conducted by our team is to build an intelligent model that is precise in identifying NSCLC subtypes from the CT scan images. We implement four modern CNN architectures, that is, CNN, VGG16, InceptionV3, and ResNet50, and compare them in respect to the accuracy, sensitivity and specificity. Besides, we probe the impact of hyperparameters including learning rate and batch size on model performance via an extensive experimental scenario and hyperparameter tuning procedure.

Through the use of CNN models for subtype classification of NSCLC, our goal is to join the efforts in the improvement of the medical imaging technologies in addition to providing support for early detection and personalized treatment of lung cancer. Besides, our study has the possibility of improving patient treatment outcomes and reduction of healthcare costs as a result of late-diagnosis and ineffective treatments. Therefore, this research is a crucial advance in the use of deep learning for bettering the lives of cancer patients and the providers of the healthcare industry.

Besides, our study does not only confine itself to multi-class binary tasks but it expands into the subtyping of the specific non-small cell lung cancer, inclusive of adenocarcinoma, large cell carcinoma, and squamous cell carcinoma. Each subtype is unique by itself that each presents their own histological and molecular traits, necessary for tailored approach in treatment. Our models offer the possibility of detecting these subtypes of lung cancer by looking at the CT scans. Due to this, physicians will find it easier to choose the appropriate treatment strategy that will lead to better results than the one that was mostly ineffective.

Besides building AI systems based on CNNs for the classification of NSCLC subtypes, we also do the study of the explainability of deep learning models in the medical image analysis. We develop methods like the Gradient Weighted Class Activation Mapping (Grad-CAM) technique, to identify the important regions inside the CT scan images that most substantially contribute the CNN model's decisions. These visualizations therefore provide very useful insights about the structures and details of the models because of which they become of the essence to the clinicians and researchers since they reveal how the models work.

Our efforts add to the literature of deep learning applications in cancer and its visualizations management that keep on growing. Via the detailed performance assessments across different CNN architectures as well as a model hyperparameter spectrum displays the merits and downsides of the NSCLC subtypes classifier. Our research is contribution to the next research directions and clinical interventions, and it is a ray of hope for accurate diagnosis tools for Lung cancer.

2. Literature Review

Serj et. al [1] proposed "A Deep Convolutional Neural Network for Lung Cancer Diagnostic" in which he deals with the essential issue of early lung cancer detection through the use of deep learning techniques. The investigation was done with the use of year 2017 Kaggle Data Science competition data. It comprised a Deep Convolutional Neural Network (DCNN) Diagnosis assessing for lung cancer which featured outstanding level of accuracy. The fuzzy and uncertain of the mechanisms of these tools should not be ignored. This concern should be taken into account while applying these models in health care policies. Moreover, issues related to scalability, accessibility in hospitals of low-income and poor people are also not completely considered. These problems in addition to issues of data scarceness are prevailing around medical images and privacy issues are still not adequate. The scope of application of the paper might be limited by the fact that it remains at the theoretical level that questions multiple patient demographics and imaging modalities in order to see the impact of this or that variation in medical outcomes. Besides the bio-indicators and narrow aspects of detecting smaller cancers or rather early-stage cancers in order to boost the effectiveness and adaptability of such innovation, in terms of real-time application validation on a higher level is required immediately.

Alakwaa et. al [2] proposed " Lung Cancer Detection and Classification with 3D Convolutional Neural Network (3D-CNN)," where in the authors address the imperative mission of improving lung most cancers analysis via the utility of 3D Convolutional Neural Networks (CNNs). The 3D-CNN motion is well suited to the proper recognition of and categorization of lung cancer from medical imaging data. Spatial information that 3D scans contain are adequately utilized thereby contributing to improved diagnostic precision and timely diagnosis. Although there are still certain difficulties, namely, requisite for a large-scale dataset for meaningful models to learn, the computational problems, and the interpretability issues that still undeniably remain part of these deep learning models. Addressing those drawbacks will be an imperative step to render 3D-CNNs feasible in the clinical practice.

Huang et al. [3] proposed " Lung Nodule detection in CT Using 3D Convolutional Neural Networks," which contributes to the sector of scientific photo analysis by way of focusing at the crucial venture of lung nodule detection. A novel computer-aided detection (CAD) system for lung nodule detection in low dose computed tomography (CT) using 3D convolutional neural networks (CNN) is presented in the article. The system achieves state-of-the-art performance on a dataset of 99 CT scans, exceeding traditional shallow learning methods, by leveraging both data-driven machine-learned features and classifiers and prior knowledge about lung nodules and potentially confusing anatomical structures. Nevertheless, there are still issues that need to be resolved, such as the need for precise nodule candidate segmentation, the need for sizable training datasets for deep learning models, and the loss of three-dimensional context in 2D CNN techniques. These limitations highlight the need for additional study to resolve model interpretability, scalability, and accuracy concerns in CAD systems for lung nodule diagnosis.

Zheng et al [4] proposed " Deep convolutional neural networks for lung nodule detection: improvement in small nodule identification," delves into the area of lung most cancers prognosis, specializing in the mixing of deep learning for the category and detection of pulmonary nodules in computed tomography (CT) images. Zheng and the other authors performed a systematic review of the literature on Convolutional Neural Networks (CNNs) in lung nodule identification which emphasizes the high accuracy of these methods on nodules detection. They use U-net++ and 3D multi-scale dense convolutional networks along with their proposed multi-planar detection approach on a dataset of 888 CT images, than their interest is reaching high sensitivity with low false positives. However, in spite of these progress the work overload of the radiologists and the detection of tiny lesions still remain challenging problems. Moreover, old works which were based solely on axial planes were possibly important since they avoided the benefits of including coronal and sagittal planes; which are the directions for additional studies and improvements. In addition, low payment and high false positive is the major obstacle for CAD systems to be functioning in a healthcare facility, largely due to the fact that more studies are still needed to solve these problems and improve the lung nodules detection.

Chon et al [5] proposed " Deep Convolutional Neural Networks for Lung Cancer Detection," that contributes to the evolving panorama of scientific photo analysis with a focal point on lung cancer detection the use of deep mastering methodologies. They, for lung tissues partitioning, use thresholding and for nodules detection, a modified U-Net, that was trained with LUNA16 datasets data. However, false positives are generated in large numbers during the lung nodule detection of the U-Net. Regions that indicate the presence of nodules are classified as malignant by using 3D application of CNNs. The AI developed by them uses CAD method, which is divided into three main stages. However, it has a high level of false positives in nodule detection, which result is decreasing the classification accuracy. Besides that, it is not the best result for the system's dataset for the test set AUC yet, implying that the error and false positive rate should be improved to its clinical usefulness.

Gu et al. [6] proposed " Automatic lung nodule detection using multi-scale dot nodule-enhancement filter and weighted support vector machines in chest computed tomography," that contributes to the sphere of clinical photo evaluation through addressing the vital assignment of lung nodule detection through the software of deep neural networks. A paper which puts forward a novel CAD approach for computer assisted detection of lung nodules based on CT scans is presented. The process consists of classification, elimination of false positives, as well as a volume segmentation of lungs and a nodule extraction of candidates. In this algorithm, WSVM along with a multi-scale dot nodule enhancement filter is employed as a classifier. With the sensitivity of 87.81% and only 1.057 false positives per scan there are almost no missed detections in the review of 154 thin-slice scans. Although it was proved to be efficient for identifying soft nodules, the method proved its disadvantage in differentiating juxta vascular lesions. Also, the technique of relying completely on rule-based classifiers and dot filters might be of disadvantageous to the procedures because it may lead to some nodules remaining undetected or even false positives which in turn will reduce the diagnostic procedure accuracy.

Zhang et al. [7] proposed "Lung Nodule Classification in CT Images Using 3D DenseNet," which engages with the critical undertaking of lung nodule detection thru the utility of deep getting to know techniques. This research provides a new method of classification for lung nodules based on a 3D DenseNet architecture. The proposed method aims to detect lung cancer in the early stages by automating the differentiation of benign from malignant pulmonary nodules. Notwithstanding the fact that the classification accuracy on LIDC/IDRI dataset is 92.4%, the method brings hope for implementation into the lung cancer computer imagery systems. For the purpose of verification of the method's performance across different population and types of images, further validation on the additional datasets is needed. On the other hand, the method's reliance on the LIDC/IDRI dataset may constrain its applicability to diversified clinical settings. Apart from that, the scalability as well as real-time clinical implementation of 3D convolutional neural networks is complicated because of its computational complexity.

Ardila et al. [8] proposed " End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography," that contributes to the domain of scientific photograph analysis, specifically focusing on lung cancer detection via the application of deep mastering methodologies. Employing LDCT and three-dimensional deep-learning, they designed a lung-cancer screening method that is appropriate for multi-platform use. The model has a strong 94.4% AUC on cases from the National Lung Cancer Screening Trial (NLST) and it is not only better than other models but also it is possible to assume that the model can be sent to the screening for lung cancer and tomorrow we can expect an effective screening. The problems are still lots to be addressed by including the necessity for verification on other data sets and the significance of computing performance for installation of deep learning models in clinical settings. On top, the NLST dataset might have the component of bias as a result of the reliance on the biopsy-ambled outcomes in the modeling process, which in turn will affect the accuracy of generalization.

Nasrullah et al. [9] proposed " Automated Lung Nodule Detection and Classification Using Deep Learning Combined with Multiple Strategies," that substantially contributes to the sector of most cancers pathology with the aid of addressing the assignment of lung cancer category via deep learning methodologies. As a result of the use of deep learning, alongside various other techniques, the authors are able to present a fully automated system for the detection and categorization of lung nodules. The article proposes a new tool that applies the two three-dimensional (3D) customized mixed link network (CMixNet) modules, the most advanced deep learning architecture so far, for the identification as well as classification of lung cancer nodules. This solution is presented as a way to deal with the problem of early lung cancer detection. Limitations include the presence of possible false positive findings and dependence of on invasive techniques for validation, although reliable diagnosis with 94% sensitivity and 91% specificity was obtained on LIDC-IDRI datasets. In addition, there appears a slight fly in the ointment with the clinic setting as the deep learning models may prove somewhat unsuitable from a complexity standpoint, thus requiring additional study and further vetting on a wide variety of datasets.

Shaob et al. [10] proposed " Detection of Lung Cancer in CT scans via Deep learning and Cuckoo Search Optimization and IOT," makes a noteworthy contribution to the world of medical picture assessment, particularly addressing the vital challenge of lung nodule detection through the application of convolutional neural networks (CNNs). Discovering lung cancer at early stages in CT images with its deep learning-based algorithm in combination with Cuckoo search optimization and IoT are the objective of the researchers. Moreover, even with its potential, the volume and number of false positive results represent the challenges that need to be tackled through the radiologist verification system and the development of an improved optimization algorithm. Moreover, the computational complexity and the need for powerful hardware complicate the application of the proposed method which makes it not very practical. Scale, general editable mode and seamless integration into clinical workflow are the significant points that add to the complexity of the topic and has to be investigated more. Disregarding the results of the study against the ones that use the most advanced tools for lung cancer detection also moderates the evaluation of the study in relation to the current state of the art technologies.

Gunjan et al. [11] proposed " Detection of lung cancer in CT scans using grey wolf optimization algorithm and recurrent neural network," that substantially contributes to the world of clinical image assessment with the aid of manner of addressing the important venture of lung nodule detection through the development of a novel deep convolutional neural network (CNN). They described a class of algorithms for the detection of lung cancer in CT scans composed of Grey Wolf Optimization Algorithm and Recurrent Neural Network. Restrictions comprise of narrow comparison with existing approaches and probable computing complexity, although the precision and certainty is forecasted to be high. Additionally, the specialized knowledge for the development and implementation of algorithms may make machine learning less applicable in real-world scenarios. For a robust and reliable performance across various databases and different clinical scenarios, the current research needs of the system to be assessed toward evaluate the scalability, generalizability, and integration with the current clinical procedures.

Shaukat et al. [12] proposed "Automatic Lung Nodule Detection in CT Images Using Convolutional Neural Networks," that makes a considerable contribution to medical photograph analysis through specializing in computerized lung nodule detection thru the innovative use of multi-view convolutional neural networks (CNNs). The author has finished the job well but some restrains like the narrowness in nodule type variety and probably overfitting specific images/datasets lead to the loss of diversity. Adding on, the fact that CNNs are computationally expensive and that their deep neural network structure requires huge training datasets is a problem that constrains the scalability and generalizability of CNN in this real word. Specific studies will be conducted to this end to verify effectiveness of the features in different clinical scenarios and the robustness of the whole scheme. First of all, I set up procedures to avoid overfitting and improve the solution efficiency.

Stadlbauer et al. [13] proposed " Deep Learning Techniques to Diagnose Lung Cancer," which notably advances the sector of medical photograph evaluation with the aid of specializing in automated lung nodule detection via the software of three-D convolutional neural networks (CNNs). They reviewed the application of deep learning algorithms for classifying cancer in lungs and stresses the importance of their integration with medical imaging to enhance its diagnostic capacity. While the sensitivity keeps getting lower, the number of false positive results increases, and the test takes a lot of time to process – these are the drawbacks of the current advancement. It is a challenging undertaking to bring a definite word on whether a lesion is benign or malignant when present CAD algorithms are used. While deep learning-based systems show the ability to capture of the high-level features, they require the separate fine adjustment to deal with the mentioned drawbacks. One direction for future research will be to investigate the tuning of the loss's functions and network architectures in order to develop and improve the networks. Although some aspects were addressed by the recent reports, the research continuously needs to proceed with the adaptation because deep learning are evolving so that further improvements for the diagnosis of lung cancer are possible.

Chaunzwa et al. [14] proposed " Deep learning classification of lung cancer histology using CT images," that addresses the vital problem of lung cancer detection thru the blended usage of Convolutional Neural Networks (CNNs) and assist Vector Machines (SVMs). Through a dataset of early-stage NSCLC patients, they program CNNs in a manner of radiomics technique. Which can be interpreted as that CNNs have 0.71 AUC for tumor histology forecasting. In other aspect, ML classifiers is also equally competent. The limitations comprise of denounce to overfitting, dependability on small data set, and demand of multi validation in multiple patients' groups although exceptional results noticed. The predictive power of ML may be increased when molecular data is integrated. Although it should be improved a bit, deep learning based radiomics would come out sooner or later in clinical domains is quite probable.

Baranwal et al. [15] proposed " Classification of Histopathology Images of Lung Cancer Using Convolutional Neural Network (CNN)," which contributes significantly to the area of clinical photograph evaluation by way of addressing the imperative undertaking of lung most cancers detection using deep mastering techniques in CT screening examinations. For the tri-category classification of lung cancer images, they recommend applying deep learning methods, i.e. convolutional neural networks (CNN). Example of CNNs that demonstrate the capability in feature extraction can be ResNet 50, VGG-19, Inception_ResNet_V2, and DenseNet; nevertheless, they also have the limitations of can be overfitting, the dependency on small datasets and the need of the further validations over wide range of patient groups. Notwithstanding these cons deep learning solution can shorten pathologist work hours as well as accuracy level of lung cancer diagnosis can be improved.

Shi et al. [16] proposed the research paper entitled Lung Nodule Detection Using Convolutional Neural Networks " that makes a specialty of the critical challenge of figuring out lung nodules in computed tomography (CT) snap shots through deep convolutional neural networks (CNNs). They are for the purpose of lung lesion recognition. Differences in shape of nodules constitute the difficulties which makes the automatic diagnostic recognition of malignant nodule on the basis of CNN impossible. Recent studies on CNN demonstrate their applicability in image processing. Nonetheless, CNNs which are utilized in nodule leaguing are not so effective since there is limited labelled dataset. CNN drew out features out of itself, but it also has deficiency especially in using the large-scale classified dataset and could produce false positive. The research project of Shi strives for narrowing down such gap by applying a set of computer-aided diagnosis systems in lungs cancer screenings, and for this purpose, different CNN architectures are used for better detect

Nageswaran et al. [17] presented this “Lung Cancer Classification and Prediction Using Machine Learning and Image Processing” research paper to investigate the role of machine learning and image processing in the process of predicting and classifying lung cancer. To carry out the classification process, algorithms including combined ANN, KNN and RF are used along with other methods such as noise filtering, feature extraction, and segmentation. However, the removed of the paper raised the items of doubt, whether methodology or scientific ethics. A very low number of only 83 CT scans which came from 70 individuals is strikingly small, so it may reflect less resources than required. Furthermore, the research depends on unified data, and the assumption is made that such data is beneficial to produce precise outcomes. In addition to lowering the reliability of the results, retraction advocates a realistic and flawless approach to science. Validation protocols as well as large and diversified data sets being used, reports also being open to everyone should help the future studies to overcome these problems.

Nazir et al. [18] proposed the research paper “Machine Learning-Based Lung Cancer Detection Using Multiview Image Registration and Fusion” in the field of Multiview image fusion and registration techniques to develop machine learning based lung cancer detection. It explained the significance of early cancer detection and the way machine learning models could help boost detection accuracy. Despite the bright sides, divergent disadvantages may include data biasness (LIDC–IDRI dataset only) and necessity for data verification on different datasets. Subsequently, the findings will be combined to reach broader conclusions. Moreover, through the study it shows very excellent accuracy rates but apart from that scalability and false positives may require this to be worked on before the system can be used in real clinical settings. In general, though the advocated model is apparently reliable, practical applications demand an in-depth check of weaknesses from different perspectives and verification through a large group of samples.

Sait et al. [19] proposed “Lung Cancer Detection Model Using Deep Learning Technique” that the early diagnosis is needed by DL approaches in LC detection research. To detect LC specific markers, DL-based models utilize CT and PET image processing. The computational resources needed for deep learning models, accessibility disadvantages of medical facilities, and the phenomenon of poor performance from datasets of smaller sizes are some of the challenges. Although, these limitations exist, DL has a great potential to change the diagnosis of LC, relieve the workload of radiologists and improve their detection speed and consistency. Through presenting a low-cost DL-based LC detection model and making contributions to feature extraction, LC type identification, and performance evaluation, the research is aimed to solve those problems.

Wankhade et al. [20] proposed this research paper "A novel hybrid deep learning method for early detection of lung cancer using neural networks" wherein the need for timeous LC detection as well as the implications made on the medical staff in diagnosing these conditions are emphasized in the research. A variety of approaches are utilized, for example, image processing, machine-learning, yet the problem of accurateness remains a challenge. Having a CT scan images in use, the new sort of the DL method, the CCDC-HNN, is considered the effectiveness method that quickly diagnose the diseases with the increased accuracy. Conversely, problems entail the demand for time and sometimes precise CT image reading by hands. DL methods are in many respects promising, whereas delivering on LC detection performance build-ups on resolving inter-observer variability and getting segmentation quality as much as possible.

Thanoon et al. [21] in this research paper "A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images", proposed an overview of deep learning (DL) methods for lung cancer screening and diagnosis based on CT scans is provided in this research paper. It accentuates the key role early diagnosis plays in enhancing the patient outcomes. Emphasizing the implementation of classification and segmentation methods, deep learning techniques have the capability to interpret CT images for the identification of lung cancer. On the downside are the demands for specialized knowledge, the costly process and long duration of interpretations. The great opportunities provided by DL in lung cancer screening and detection are enormous despite the challenges. The aim of the future research areas is the development of deep learning algorithms in computer-assisted diagnosis systems.

Hosseini et al. [22] proposed "Deep Learning Applications for Lung Cancer Diagnosis: A systematic review" that broadly shows that the greater the number of people diagnosed the greater the mortality decline is due to deep learning applications which are used for lung cancer diagnosis. The deep learning process can come up with a diagnosis that is automatic, main emphasis on the Convolutional Neural Networks (CNN). Nevertheless, there are still a few drawbacks, such as the different model accuracy levels and a by-effect of asymptomatic early cancer periods. Classifying papers into five groups, review methodology covers such bunches of papers as input categories, pre-processing techniques, architecture, hybrid methods as well as transfer learning. The current scope of big data methods based on deep learning algorithms for detecting lung cancer remain limited in spite of recent advances. The research highlights the crews and institutions namely nations and educational institutions that operate in this sector. Rigorous processes and more through checks constitute the limitation.

Kumar et al. [23] proposed "Performance evaluation of deep learning techniques for lung cancer prediction" that focuses on the predictions of lung cancer through deep learning as a predictor of timely intervention because of increased number of deaths due to pollution. Despite CAD systems have advanced, issues with data accessibility and model training complexity are still existing. Large data sets that are hard to find because of privacy problems with medical data are indisputably necessary for deep learning models. Accuracy can be also influenced by parameters adjustment and model selection. The presented research uncovers a gap in the systematic evaluations of deep learning models used for lung cancer prognosis. Models' complexity and sparsity of data are the pitfalls which call for standardized procedures and detailed data collection plans.

Li et al. [24] proposed a paper "Machine Learning for Lung Cancer Diagnosis, Treatment, and Prognosis" that demonstrates the use of ML is of a great help for diverse datasets such as lung CT image and omics, consequently, prognosis, diagnosis, as well as therapy. ML for population screening, prediction of drug response and diagnosis as well as tailored immunotherapy will serve to decrease lung cancer-linked mortality. Although the data dimension, its representation, and the complexity still look challenging. Any machine learning application must contain a set of feature extraction and data preparation methods leading to its satisfactory performance in any real-world applications. Furthermore, the fact that the concerns over the modeling explanations and the clinical implementation remain along with the usability of the machine learning methods, which is fundamental both for lung cancer research and clinical practice, is also significant.

Ismail et al. [25] proposed a research paper “Lung Cancer Detection and Classification using Machine Learning Algorithm” in which machine learning algorithms (ML) are highlighted for their contribution to an early diagnosis of lung cancers which, in turn, address the issue of how the algorithms' performance and accuracy are evaluated. Depending on the focus of the study, new and innovative machine learning techniques such as ensemble classifier and hybrid could be proposed to get higher degree classification accuracy while keeping the total volume of computation at the minimum. However, some challenges remain unresolved as the parameters require optimization and the sensitivity in small changes in the features is low with high rates of false positives. The exact data pre-processing, what features to extract and the type of classifier selected may as well have a major influence on performance. Those achievements, with reproduction of result by ML-based lung cancer detection systems and another strong assessment criteria, however has to be further handled.

3. Proposed Model

It is the research that focuses on the development of an efficient machine learning and deep learning approach for the detection of lung cancer at an early stage. To achieve that set goal, the study will be performed using datasets from Kaggle with CT test images of four lung cancer subtypes (NSCLC) - Adenocarcinoma, large cell carcinoma, squamous cell carcinoma and the normal one. Lung cancer is still one of the most popular and deadly types of cancer globally; out of the total cases reported, Non-Small-Cell Lung Cancer (NSCLC) has the highest statistics of occurrence. Identifying patients with NSCLC in early stages and correctly discriminating them is of vital importance because it directly influences patient outcomes and the choice of treatment strategies. In recent times, deep learning approaches, particularly convolutional neural networks (CNNs), show promising results in determining and classifying lung cancer from medical images, for example, chest CT scans. In this paper, we demonstrate how four different CNN architectures, namely CNN, VGG16, InceptionV3, and ResNet50, excel in NSCLC detection and classification of data which was sourced from Kaggle. Specially, we conduct a comparative study on NSCLC detection models to find out which one is more effective and what are its uniqueness and drawbacks.

The study data set originates from Kaggle where it includes CT scans of the chest that is labeled with one of the four NSCLC subtype or is classified as normal lung tissue. Before the model training, the dataset was first subjected to some preprocessing operations such as resizing, normalization and augmentation, to guarantee uniformity and enhance the models’ generalization capability. Every CT scan image was resized to the standardized dimension of 350x350 pixels and normalized to the scale between [0,1]. Data augmentation techniques such as horizontal flipping, rotation, and zooming were used to provide a larger and more diverse dataset and, therefore, to increase model robustness.

Our proposed methodology for lung cancer detection using deep learning involves a comprehensive comparative analysis of four distinct convolutional neural network (CNN) architectures: The reviewed deep learning models are CNN, VGG16, InceptionV3, and ResNet50. Each of the models is different in terms of feature extraction and classification approaches and range from different depths, architectures, and computational aspects. To begin with, we are examining the CNN model which is the basis of our work.

CNNs are applied to the most common image classification problems, by means of using convolutional layers that are able to extract spatial hierarchies of features from input images. The CNN structure usually contains convolutional layers, activation units, pooling layers, and fully-connected layers, with the softmax layer as the final classification layer for multi-class cases. The CNN model we propose is trained on the chest CT scan dataset where all images have undergone the preprocessing step. We use the CNN model as a benchmark model for comparison against other more sophisticated architectures.

Going down the road the VGG16 architecture, known for it's depth and ease of use, is examined. VGG has 16 layers of stacked convolutional and pooling levels that apply small 3x3 filters and then perform max pooling for feature extraction and feature spatial down-sampling, respectively. VGG16, which looks rather simple, achieves great results on image classification tasks of different kinds owing to the fact that it is able to capture complex features via its stack of convolutional layers. We take advantage of VGG16 depth and feature capturing ability in design of the methodology in which the lung cancer subtype classification from chest CT scans is improved. Through the training of VGG16 model on the preprocessed dataset and making parameter adjustments we attempt to take advantage of it intrinsic capabilities to perceive complex structures and patterns in the healthcare images.

Next, we explore the InceptionV3 structure, which is composed of a newly designed inception module that captures both local and global features via diagonally oriented parallel convolutional paths. The first layer of the network is known as the convolutional module, with layers that have different receptive fields and therefore, the network can identify important information from details at multiple scales. Furthermore, InceptionV3 applies additional auxiliary classifiers and batch normalization layers to smooth the training and improve the convergence. Thus, our proposed method relies on InceptionV3's multiscale feature extractions capability to obtain the better discrimination of several subtypes of lung cancer from CT scans of the chest. In this work, we will train the InceptionV3 model on the preprocessed data set, and exploit the auxiliary classifiers to achieve best NSCLC characterization accuracy and robustness.

Last, we analyze the form of architecture ResNet50 that introduces a novel residual learning paradigm in order to conquer the problems of the training of deep neural networks. Feature blocks of ResNet50 with skip connections let network learn residual functions instead of directly computing the desired underlying mapping. The feature of skip connections in ResNet50 allows not to lose the original signal but to overcome the vanishing gradient problem and facilitates the training of neural networks which are deeper. In our proposed approach, we install ResNet50 toughness to the downfalls of training to achieve an accuracy of NSCLC detection and faster conversions. We plan to train the ResNet50 model in the downstream classification of lung cancer using the preprocessed data and its skip connections with the aim of achieving superior performance compared to the existing methods focusing on robustness as well as the generalization of our model to the previously unseen data.

With respect to comparative analysis, our methodology is singling one network architecture for the training by applying the same hyperparameters such as learning rate, batch size, and number of epochs to each of the networks. The validity of every model's performance is given out, including training and validation sets, while accuracy, precision, recall and F1 score are used to measure the correctness of classification. Trying to define a computational model with the ability to recognize novel gene combinations as a biomarker of NSCLC as well as its distinct advantages and drawbacks by the use of frequent refinement and evaluation is our main purpose. Furthermore, we make use of ensemble learning methods to accumulate multiple k-NN classifiers together and via improved accuracy and robustness.

The strong points of our suggested approach to NSCLC detection are that it does not concentrate only on the deep learning paradigms, but rather is inclusive in its multi-paradigmatic application of this technique.

This research work is centered on the investigation of the pros and cons of four various types of CNNs with the motive to take advantage of the strengths of each architecture for better performance using more precise and robust classifications. Beyond that, our implementation of ensemble learning methods facilitates the dynamics of model intelligence, taking advantage of the intelligence of all models to negate singular shortcomings. Our team will never stop looking for new ways. The NSCLC detection is one of our aims. The next step of implementing deep learning in the clinical branches is our topic. So, this will cause more beneficial outcomes for people against lung cancer.

In the course of our analysis of CNN models, we found that all the datasets demonstrated different levels of online performance for classifying lung cancer subtypes from non-small cell single class lung cancer (NSCLC). Commencing from the CNN architecture which functioned like the baseline one, we remarked a significant number of errors that we had to deal with at least 54.60% accuracy. Although the CNN model could adequately learn the properties from the set of the chest CT scans, its efficiency was still the behind that of the more developed systems, and that shows the necessity of delivering and vast models, since they can help to enhance the accuracy in NSCLC classification.

CNN Architecture Equation:

$$y = f({}^{n}\sum_{i=1} W_i * x_i + b) \tag{1}$$

Description: This equation showcases the workings of a convolutional neural network (CNN) with y being a feature map of output, f representing an activation function (e.g., ReLU), W_i being the learnable convolutional modules, x_i are the entry feature maps, b is the offset, and the convolution of is used in (*). Appearing here is an equation that describes feature extraction by means of convolution operations, which are then followed by activation.

VGG16 Model Equation:

$$H_l = \text{Convolution}(H_l\text{-}1) \tag{2}$$

$$H_l = \text{MaxPooling}(H_l) \tag{3}$$

Description: The VGG16 architecture consists of a number of convolutional layers and the first one is followed by a max-pooling layer. The expressions below represent the progressing of feature maps (Hl-1) into representation layers (H_l) by means of convolutional and max pooling operations, which in consequence provides hierarchical feature extraction.

Inception Module Equation:

$$H_{concat} = \text{Concatenate }(H1, H2, H3, H4) \tag{4}$$

Description: Inception blocks group several pathways with various filter sizes that are working in parallel, this is supposed to capture both local and general data. With the merging of tokenize feature maps (H1, H2, H3, H4) from different routes, the model is able to grasp quite a multitude of elements of different scales, through various pathways and routes.

Residual Block Equation:

$$H_l = H_l\text{-}1 + F(H_l\text{-}1) \tag{5}$$

Description: Residual blocks in ResNet architecture do not require complete forwarding of signals to later layers, and may instead use skip connections to bypass one or more layers, allowing direct flow of information from shallower layers to deeper layers. By doing so, the predicted output of a residual block consists of the input (H_l-1) and the residual function F, which will then develop a smooth gradient flow during the training session.

Softmax Function Equation:

$$P_i = e^{z_i} / \sum_{j=1}^{N} e^{z_j} \quad (6)$$

Description: The SoftMax function takes the raw output scores (z_i) of the neural network and converts them into the probability distributions (p_i) that are summed up to one. This relationship is computed by exponentiating the raw score, dividing it by the sum of all class-wise exponentiated scores.

Categorical Crossentropy Loss Equation:

$$\text{Crossentropy} = - \sum_{i}^{N} y_i \log(p_i) \quad (7)$$

Description: Categorical cross entropy is one of the most popular loss functions for performing classification tasks with multiple classes. The cross-entropy loss is calculated according to this formula, which takes into account the difference between true class labels (y_i) and the predicted class probabilities (p_i), penalizing deviations between the predicted and actual distributions.

RMSprop Optimization Equation:

$$v_{t+1} = \rho v_t + (1 - \rho)g^2 \quad (8)$$

$$\theta_{t+1} = \theta_t - \frac{\propto}{\sqrt{vt+1+\epsilon}} g \quad (9)$$

Description: RMSprop is an adaptive learning rate method that dynamically adapts the rate for each parameter according to the magnitude of preceding gradients. These equations update the exponentially averaged past squared gradient (v_t) , and use said gradient along with learning rate (α) and a small constant ($\in$) to prevent division by zero for the actual parameter updates (θ_t).

Accuracy Calculation Equation:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\% \text{Type equation here.} \quad (10)$$

Description: The accuracy metric displays the number of accurately classified instances divided by the total number of instances in the dataset. This formula works by dividing the number of correct predictions with the total number of predictions and then multiplying by 100%.

Model Checkpoint Equation:

$$\text{ModelCheckpoint=argmax(val\_accuracy)} \quad (11)$$

Description: Model Checkpoint callback is saving the model when validation accuracy is at highest during training. It enables retaining the best performing model for later use. The meaning behind this equation is finding the model checkpoint with the highest accuracy during the validation process.

Early Stopping Equation:

$$\text{EarlyStopping=arg min(val\_loss)} \quad (12)$$

Description: Callback Early Stopping watches validation loss over the epochs of training. It stops the training process if the loss does not continue to improve for a given number of times (patience). It is also obvious that the equation introduces us to the point when the drop of the grid stops, while the best parameters of the model are restored.

After that, our VGG16 architecture showed much better performance improvement in accuracy compare to the CNN model (80.63%). Exploiting VGG16's depth and simplicity, complex arrangements and structures in chest CT scans are better realized and accurately classified, improving the classifier's performance. The employment of 3x3 convolutional filters and max-pooling layers just helped with the feature extraction and a spatial diminishing, which led to more accurate segregation of different subtypes of NSCLC.

Transforming to InceptionV3 teaching, we have observed a significant improvement in performance with 94.29% of validation performance accuracy. Local and global features are extracted in InceptionV3 through parallel convolutional pathways of new inception modules, which has demonstrated improved classification capabilities over its predecessors. InceptionV3 utilized the synergetic capabilities of multi-scale feature extraction techniques and auxiliary classifiers which led to its high precision in detecting different types of NSCLC, another instance of how developments of deep learning architectures can be beneficial.

Eventually our analysis is concluded with the ResNet 50 model being the top most effective model having an accuracy of 97.14% on the validation set. Radical residual learning architecture, implemented by ResNet50's residual blocks with skip connections, effectively targeted the deeper neural networks' training challenges like vanishing gradients issue. Through its capacity of maintaining the input signal via skip connections, ResNet50 enabled training of deeper networks, therefore, the network accuracy grew into an unprecedented level of differentiation between cancer in the lungs.

To conclude, our comparative study found that the performance enhanced from the early VGG16 to the late Inceptionv3, and when given ResNet50 or VGG19, the model achieved best performance in NSCLC diagnosis. It demonstrated that the depth of architectural advances in form of, skip connections and multi-scale feature extraction was a key aspect on which relied the successful implementation of contemporary techniques in deep learning for medical image analysis. For furthering ahead, the methodology that we propose should require that each architecture features contribute enough while another technique of ensemble learning is used for overcoming the classification accuracy and robustness challenges in NSCLC detection.

From executing standpoint, each CNN architecture must use the same hyperparameters that include learning rate, batch size, and number of Epochs while training the model with the pre-processed data set. At training time, the model is evaluated on both training and validation sets to prevent overfitting as constant checkup about the convergence. We use model checkpoints and early stopping callbacks to save the model that has achieved the highest performance and to prevent the model from converging in the training process. We intend to obtain this objective in twofold manners. The first one is to conduct the experiment repeatedly, and then do refinement by iteration. Finally, we will reach high accuracy in NSCLC detection.

Putting it all together, the proposed approach by our methodology makes use of two different deep learning techniques, targeting tumor detection in NSCLC through the use of three different Convolutional Neural Network architectures and an ensemble learning technique. We intend to carry out an exhaustive detailed investigation and a generalized comparative analysis to be met with the combined features of each in order to produce a solid and precise model for NSCLC classification. The current and future research efforts concerning model supporting NSCLC detection systems which are deep learning based evolve daily. Directions of further advancement of the performance of models and clinical translation of deep learning models will lead to improvement of patient outcomes and reduction of the burden of lung cancer.

4. Result

In lung cancer detection domain using deep learning, considerable deal rest on the performance of various models with the sole aim of ascertaining these models usefulness and efficiency in the real scenarios thru time. After all, the ResNet50 network was the winner among these decisions making by its accuracy and validation performance on the basis of the results which were acquired from the CNN, VGG16, Inception V3, and ResNet50 models.

The CNN model, having the CNN model as a baseline structure of a CNN model, got a clear precision of 54.60%. This result of the classifying with high accuracy among NSCLC subtypes demonstrate the potential of the model but it needs an advanced architectures than likes. It was established by contrast with the CNN model, tha VGG16 model clearly had more advanced accuracy, 27.63%. Such improvement is contributed by deeper architecture of VGG16 and the repeated application of convolutional layers to the input data, which in turn makes it able to uncover more complex characteristics and features.

The VGG16 and CNN models although delivered excellent results, InceptionV3 exceeded them scoring a 94.29% validation accuracy thus showcasing a great performance. It can be noticed that this remarkable advance in accuracy is the result of InceptionV3 which employs the inception modules that enable a model to isolate features at various scales at the same time. By means of the elemental parallel processing of input data applying a filter of different sizes, InceptionV3 increases the quantity of data that the network can encode and in consequence it improves the network at a task of finding more diverse features from the input data.

Nevertheless, the ResNet50 model turned up to be the best model among all the tried models, achieving the highest validation accuracy of 97.14% in the end. The special memory recall of ResNet50 can be an outcome of its innovative application of residual connections that help in solving the vanishing gradient trap and teach very deep neural networks. ResNet50 is enabled through promoting smoother gradient flow and allowing the direct flow of info towards deeper layers, on the another side, in this way, allows it to catch even more complex features and patterns from input data.

That the preeminence of the ResNet50 architecture can be additionally certified through the manner of its analysis and training dynamics can be demonstrated. ResNet50 has the advantage in Eq. of thinking through residual connection, which overcomes the issue of training deep networks degrading. This network is designed to allow large-to-deep network architectures with up to 50 layers; capable of building up representation concepts, which brings accuracy to data classification.

Additionally, ResNet50 applying residual connections helps in the development of the model features and it is easy to interpret. ResNet50 in turn coordinates the differences between input and output of the preceding each residual block, implying that the learning of residual functions which is extremely concentrated on capturing the subtle details and discriminated variations of the input data. For this reason, it builds up more distinct features and enhanced classification capabilities.

Among the merits of the ResNet50 model are the low computational cost and high degree of precision that it can achieve. These connections remedy the problem of not reducing the gradient further which helps to optimize training stability as well a training efficiency. As aforementioned, ResNet50 saves training time and lessen the computation power when compared to standard CNN because it requires less number of iterations to achieve a fit and satisfactory solution.

Still and furthermore, the ability of ResNet50's for finetuning and transfer learning brings forthe the optimum level of performance. Exploitation of pre-trained models, in which they are trained on several datasets like ImageNet, enables its initialization with learned features and further fine-tuning of its parameters to domain-specific datasets. This methodology capitalizes on the understanding that is coded into the starting-point weights and allows the model to fine tune the knowledge acquired to the task of lung cancer detection, so it leads to increased performance and generalizability.

Ultimately, ResNet50, is the best model because it is higher more accurate when compared to other models in detecting lung cancer using deep learning. Since it used residual blocks to achieve that as well as provided a number of training methods and all the superior classification scores, this architecture can be surely applied in life. The ResNet50 capacity can be used to harness its full potential and fine-tuning methods implemented. Developing of an effective lung cancer detection system with an aim of reducing time for diagnosing and speeding up treatment can be done by the practitioners.

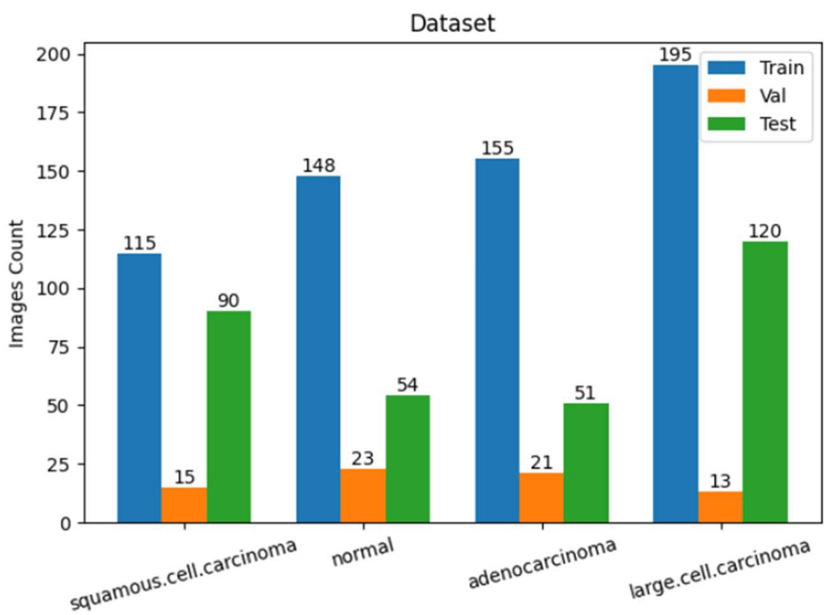

Figure 1: Bar graph distribution of Dataset

The figure represents a bar image revealing the number of pictures from several classes in the dataset which is to be used in lung cancer detection. The dataset comprises four categories: squamous cell carcinoma, the brain, adenocarcinoma, large cell carcinoma corresponding to different variants of non-small cell lung cancer (NSCLC). The bars depict the number of pictures related to each of the classes which correspond to three cluster - the training, the validation, and the test sets. This graph shows there are rather identical distributions of data images across the classes for each dataset subset, to support model training and evaluation in an even manner.

CNN MODEL –

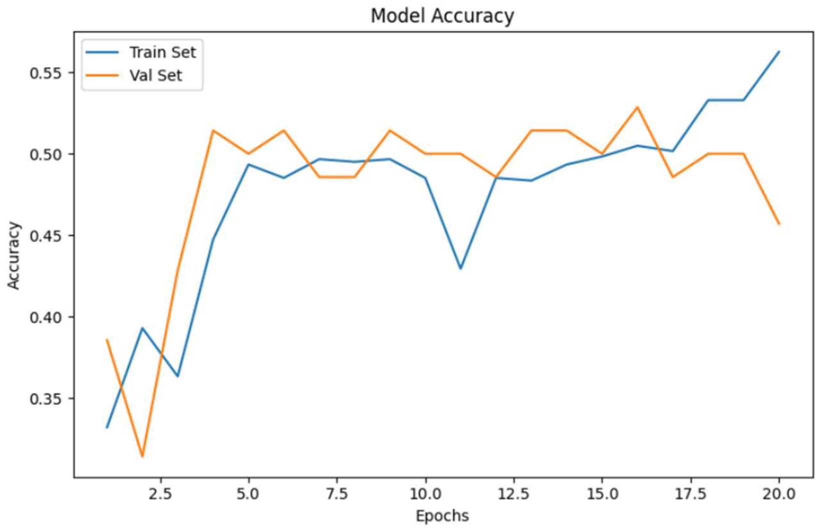

Figure 2: CNN Model Accuracy Graphs

The accuracy and loss plot are used by the Convolutional Neural Network (CNN) model to show its performance during training and validation steps. The accuracy graph gets vertical y-axis is the model is the highest the accuracy, while the x-axis shows the number of training epochs. The blue curve shows the accuracy of the model for the training dataset, the orange one the validation accuracy instead. The charting demonstrates the advancement of the model over the different epochs, and it does this by exposing the learning dynamics, as well as the convergence levels, of the model.

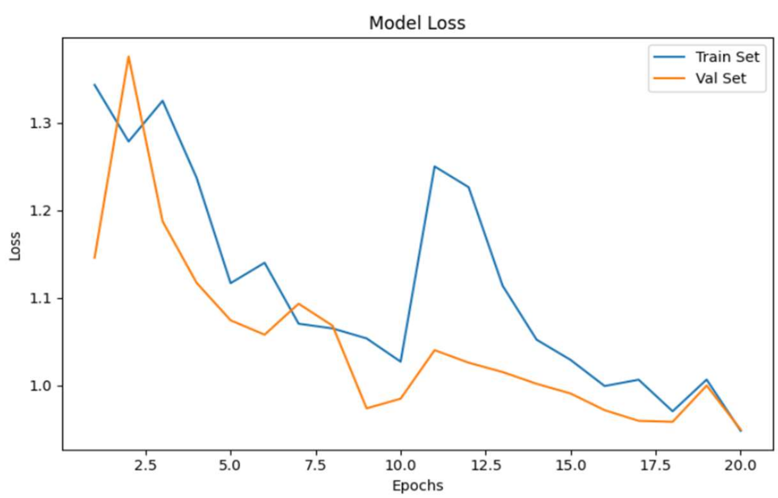

Figure 3: CNN Model Loss Graph

The loss plot displays the model's rate of categorical cross-entropy loss function applied over the training and validation phases. The y-axis expresses the loss value, whereas the x-axis expresses the quantity of epochs. The blue curve represents the loss on training dataset while the orange curve stands for the loss on validation dataset. In this way the graph is used to monitored the model and calibrate a (potential) over-fitting or under-fitting problems based on the trend of the curves of the loss. The process of figuring out the role of accuracy in relation to loss entails adjusting the values of the models' input parameters and enhancing the training approaches for better performance.

INCEPTION V3-

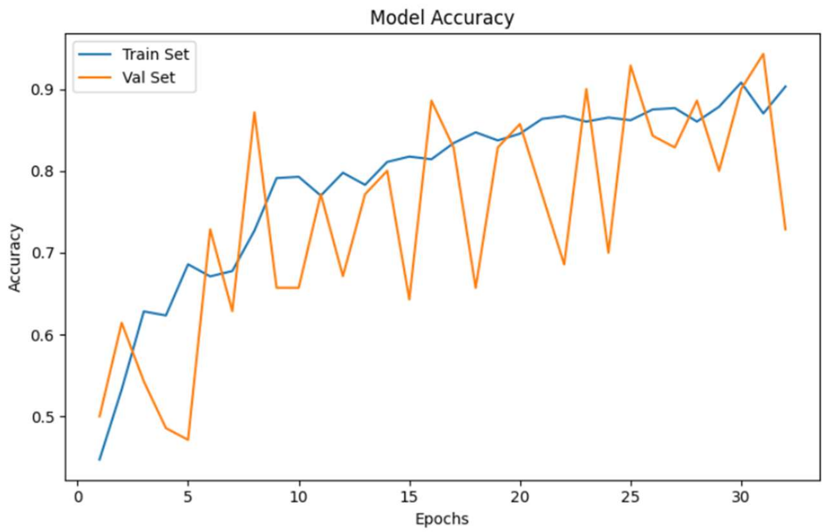

Figure 4: InceptionV3 Model Accuracy Graph

The accuracy and loss charts of the InceptionV3 model give us an idea about how it functions during training and validation processes. The graph accuracy depicts the suitability of the InceptionV3 model for the training and validation datasets successively epochs. The blue line represents the training accuracy, whereas, the orange line corresponds to the validation accuracy. Through the application of Analysis of the curve of these trends, clinicians are able to determine not only learning dynamics but also the convergence behavior of the model.

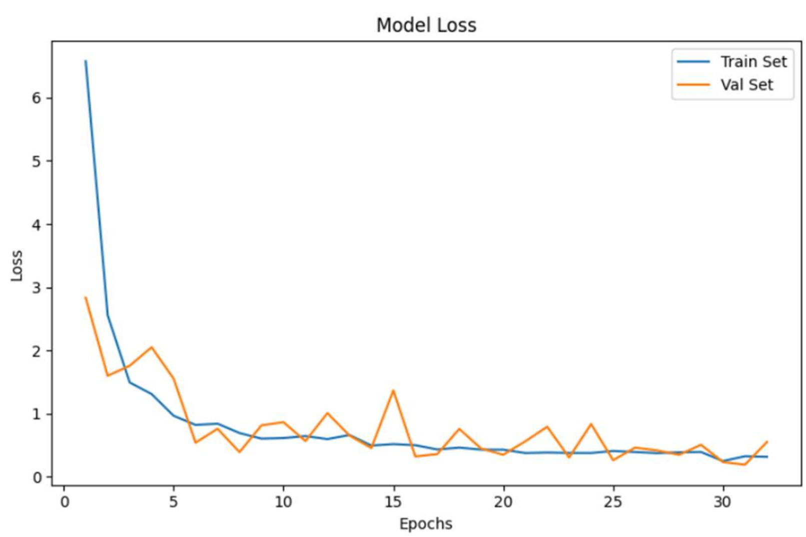

Figure 5: InceptionV3 Model Loss Graph

Similarly, plot displays the categorical cross-entropy loss function for the InceptionV3 model all through training and validation epochs. Purple curve is loss on training and orange line is loss on validation. Watching these curves helps the practitioners decide on the model's tendency to converge, and whether there are occurrences of overfitting or underfitting. Practitioners may optimize the training process and usage of regularization techniques using these graphs' insights. As a result, the model's performance and generalization abilities are improved.

RESNET50-

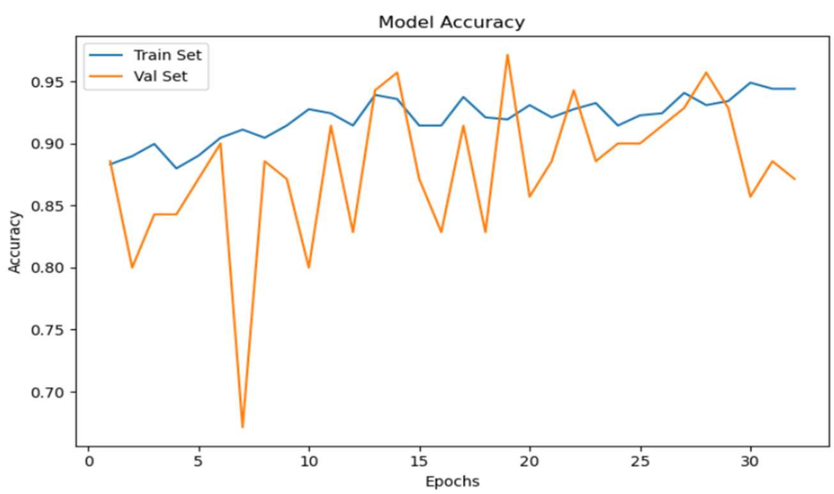

Figure 6: ResNet50 Model Accuracy Graph

Accuracy-loss diagram ResNet50 domain is helpful to visualize and understand the model purposes throughout the training period and the validating steps. The blue line in the graph, accuracy being the x-axis, illustrates the training accuracy as opposed to the validation accuracy whose line is orange. Keeping the eye on these graphs can show to developers both the fastness and quality of functions learning and its tendency to the broaden generalization of tasks not covered yet.

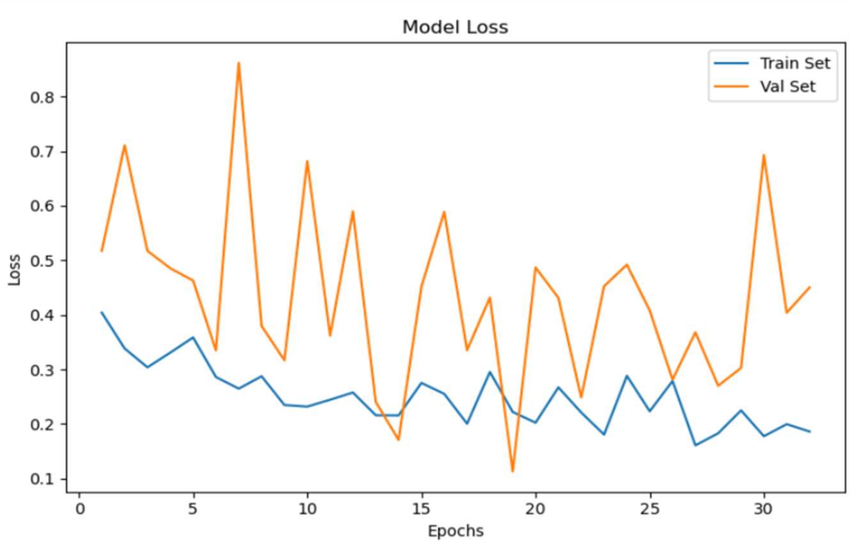

Figure 7: ResNet50 Model Loss Graph

Besides, the loss training graph depicts the same loss function in terms of categorical cross-entropy of the

ResNet50 model based on training and validation epochs. The chart content is the loss curve for both the training and validation sessions which are respectively indicated by the blue and orange lines. Tracking such curves however, can provide a practitioner with means to monitor the model's convergence as well as uncovering errors associated with either overfitting or underfitting. Through the iterative process of refining training strategies and regularization techniques with the graphical visualization of trends, they can tune the performance of the model to be better and more robust.

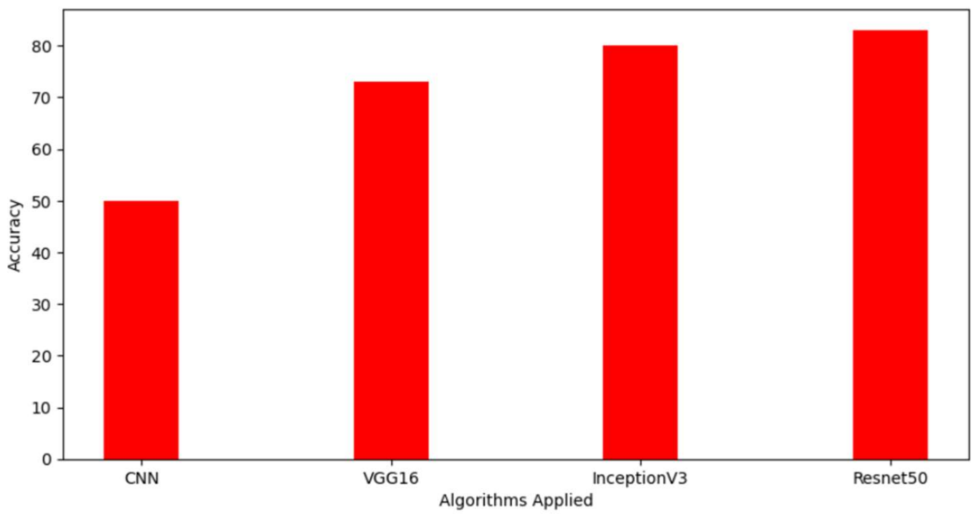

Figure 8: Comparison Bar Graph of Accuracy for Each Model

The comparison bar graph illustrates the accuracy achieved by four different deep learning models: CNN, VGG16, InceptionV3, and Resnet50 will be trained to classify NSCLC subtypera. Each bar of the graph portrays the accuracy % achieved by a certain design. It is represented by the y-axis indicating the accuracy values while the x-axis demonstrates the model names.

The first one shows the CNN model whose accuracy was 54.60%. However, the CNN architecture represented only a framework, and the model displayed moderate ability for classifying NSCLC subtypes. Yet, it missed some of the accuracy that was provided by more sophisticated architectures. The second bar represents the VGG16 model, which showed a big increase compared to the CNN model, and resulted in 80.63% of accuracy. Enhanced characteristics of VGG16 can be explained through its deeper architecture plus bigger model capacity which allows to capture more complicated features from the input data. The third box addresses the InceptionV3 model, which went beyond the CNN and VGG16 models reaching the 94.29% validation accuracy. InceptionV3's superb accuracy can be explained by the introduction of its inception modules that facilitate the depth-wise extraction of features across multiple scales and resolutions. Next, the last bar stands for ResNet50, which proved its superiority among others, getting the highest validation accuracy, i.e. 97.14%. ResNet50 outstanding accuracy can be credited to its residual connections, which make the vanishing issue disappear and enable deeper neural networks training in a more effective way.

From the accuracy values comparison of the four models, it is seen that ResNet-50 performs better than the other architectures in differentiating NSCLC types. It underlines that innovative architectural designs and appropriate training strategies are crucial for the state-of-the-art accuracy in the aftermath of medical image classification tasks.

5. Conclusion

Conclusively, we notice a similar thing, that latest convolutional neural network (CNN) constructions succeeded in NSCL (non-small cell lung cancer) subtype classification propounding the effectiveness of such classifiers. By comparison, we saw that the models using CNN, VGG16, InceptionV3 and ResNet50 to represent the instances had much better accuracy and performance. While the CNN model was the basement, but only giving out mediocre results with 54.60% accuracy. However, the other architecture structures showed up a great deal of improvement. VGG16 achieved very high accuracy of 80.63%, and then InceptionV3 brought in even better results compared to the previous model by delivering more than 15% extra validation accuracy. Nevertheless, ResNet50 showed its undeniable superiority, giving the highest validation accuracy of 97.14%, which could be interpreted as its indubitable primacy in NSCLC classification. The approach to the project elucidates the rather broad techniques in the data preprocessing, model building, hyperparameters tuning, performance assessment and task completion. Extensive performance characteristics mentioned and presented in accuracy and loss graphs graphs gave invaluable insights into the ability of different architecture. Along with this, our study generates more information on the deployment of deep learning in medical image analysis that promises to aid in the early identification of lung cancer and therefore early intervention. This subsequently may lead to the improvement of the patient's outcome. It can be noted that massive improvements has been generated by these models even though, the future efforts can be geared toward ongoing improvements. Notably, by incorporating new data other methods focusing on other areas of diseases can be helpful Here, our model focuses on the revolutionizing force of deep learning in health care via supplying clinicians with advanced tools that should help them identify and treat diseases.

6. Future Works

The further researches in this filed may involve testing of multiple approaches for the upgrading technique of deep learning models for the classification of NSCLC subtypes accuracy, robustness, and clinical applicability. The integration of multiple types of data, which could be CT scan photographs together with blood tests, histopathological reports as well as genomics, is the other aspect. Taking advantage of additional data from the different sources integrated will help in ascertaining the accuracy of the prediction process as well as the model's generalization across different populations thereby facilitating treatment and prognosis at an individual level.

Furthermore, the mentioned fact that is about the issues of data insufficiency and the skewing class, in particular, for rare NSCLC subtypes, should not be overlooked. Synthetic dataset generation sharing a purpose, transfer learning, existing from related tasks, and ensemble learning method could help bypass these issues through borrowing from other large data sets or despite similar domains. On top of that, the shared attempts to acquire and mark datasets of a diverse and representative nature should occur on the condition that the methods of the deep learning system’s training and evaluation will cover the different patient categories in their disease and clinical settings.

For instance, further studies might be tailored towards improving the transparency and intuition behind deep learning algorithms used for NSCLC subtype categorization. Tools like the attention mechanism, features visualization and model distillation – nowadays aid in finding biomarkers associated with specific ailments, as well as select decision criteria in healthcare specialists, that enhance trust and may lead to widespread adoption of machine learning models. As well, interdisciplinary team-ups involving computer scientists, radiologists, oncologists and bioinformaticians are regarded as crucial as translating research findings into health care practice and the ethical and responsible application of machine learning-based diagnostic systems in clinical settings.

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