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LUNG CANCER DETECTION AND CLASSIFICATION USING MACHINE LEARNING ALGORITHM

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Abstract:

Lung cancer is a widespread and life threatening disease that has international concerns, and requires innovative methods of identifying it at an early stage and classifying it. In the present paper, a new solution, utilizing the newest machine learning algorithms to enhance the effectiveness and accuracy of lung cancer diagnostics, is presented. The proposed solution will integrate the most recent image-processing algorithms and an effective classification model to analyze the medical imaging data as a whole. The motivation behind this study is that the literature review is done in a critical fashion and gaps that exist in the current literature are determined by this approach and opportunities that machine learning offers to medical imaging. It is this set of gaps that we are targeting, and this approach is a mixture of image preprocessing techniques, feature extraction techniques, along with a state of the art machine learning model. The implementation model is described with step-by-step processes, tools and technologies applied to train and validate on a mixed dataset. Experimental results verify our technique is effective, and the sensitivity, specificity, and the overall accuracy of the technique are better than the existing procedures. These discoveries can be significant due to the fact that they will present a useful and timely diagnostic instrument to the health professionals in order to attain better patient outcomes. In conclusion, the paper can be said to contribute to the field of lung cancer detection as well as predetermine the subsequent improvements and extensions of its application in medical imaging.

Keywords: Lung Cancer, Machine Learning, Medical Imaging, Image Processing, Early Detection

1. Introduction

Lung cancer is one of the world health risks and has a high proportion of cancer morbidity and mortality. The disease is extremely complex, hence, the need to determine the sophisticated processes of its early disclosure and accurate classification, thus, optimizing the results of its treatment. The provided paper is a good idea, which may use the benefits of machine learning algorithms to alter the status quo in the sphere of lung cancer diagnosis. Together with an excellent image processing system, which will be the best in the world, and a powerful classification system will improve accuracy and efficiency of early lung cancer detection and classification [1]. The reason why this research will be conducted is that the literature review has revealed that the current methodology of lung cancer detection has certain gaps. The classical forms of the diagnostics are usually either invasive or not sensitive enough to identify the malignant lesions within a timely manner. Furthermore, it is clear that the ever growing quantity and complexity of the medical imaging data require more complicated and efficient analysis mechanisms. We are operating at the interface of medical imaging, machine learning, and cancer research in recognition of such challenges. Recent developments in machine learning especially in computer vision have provided a pathway in medical image analytics. It is also possible to train machine learning to recognize complex patterns and abnormalities in medical images because of the availability of big data and processors [2]. The ability to extract minor features in radiological images can help far to enhance the accuracy of diagnosis in the case of lung cancer detection. The paper promotes the holistic approach that does not merely comment on the shortcomings of current models but also contributes to the reinvention of the medical diagnostics landscape.

Our proposed work is fuelled by the vision of creating an effective and reliable early-warning system of lung cancer. We rely on the interaction between machine learning models and image preprocessing methods to achieve the success of our approach. Preprocessing of images is essential in the images enhancement process that ensures the subsequent analysis is informed with the appropriate information [3]. We use an approach based on the selected machine learning algorithm that might acquire complex patterns and make informed choices concerning the obtained features. In what follows we consider the complexity of our methodology. The literature review provides us with a clear picture of the existing research that demonstrates that there are serious challenges and gaps that will be addressed through our project. The proposed work describes the conceptual framework and focuses on image processing and machine learning. The specifics of methodology and implementation explain the sequential steps, tools, and technologies that we employed in the development of the system of lung cancer detection. Our experiments are presented in the results section and demonstrate the effectiveness of the proposed method in the form of quantitative measurements [4].

Literature Survey

General literature analysis is beneficial to mention the multifaceted image of lung cancer detection methodology and define the strengths and limitations of the recent studies [5]. The traditional means are usually intrusive and lack the sensitivity of detection at an early age. As a result, one can arrive at a conclusion that machine learning in medical imaging has brought forth a new opportunity of improving accuracy and efficiency in the diagnosis of lung cancer [6]. The earliest attempts of using machine learning to analyze medical images could be dated to the 1990s, but in the last decade, much ground was made. A broad literature has studied the applicability of a variety of machine learning algorithms, such as the support vector machine (SVM), neural network and ensemble, in lung cancer detection. Smith et al. provide an example of using SVMs to extract features on CT scans and demonstrated promising sensitivity and specificity [7]. Recent works have paid some attention to employing deep learning techniques, particularly convolutional neural networks (CNNs) to the extraction and classification of features in an automatic manner. These neural networks have proven to be spectacularly effective in other image classification problems and this has made the application in medical imaging. To do so, Rajpurkar et al. utilized a deep learning model to detect nodules in the lungs in the chest radiographs automatically and best the performance of a seasoned radiologist [8].

Whereas these breakthroughs have been achieved, the interpretability and generalizability of the machine learning models of medical imaging remain challenging [9]. One common thread that has been followed in the literature is the need to have good preprocessing techniques that would enhance the quality of the image and reduce noises. Wu et al. provided an illustration of an entire pipeline of lung nodule detection during the preprocessing process, such as image normalization, lung segmentation, and noise reduction [10]. They concentrate on the necessity of preprocessing with caution as far as making additional machine learning analysis to be reliable. Besides, the diversity of datasets is a challenge that complicates the creation of universal models. Many studies have shown promising outcomes on some datasets but the problem of the implementation of the results to other populations remains an enigma. It is particularly applicable in the context of lung cancer wherein the variability in patient demographics, imaging equipment variability and protocol variability may exert considerable impact on the results of model performance [11]. There is also the recent literature regarding integration of multi-modal imaging data. Information to integrate different imaging, such as CT and positron emission tomography (PET) would have a potential to diagnose more accurately. With a hybrid model, which integrates the features of CT and PET images in the detection of lung cancer, the researchers, Huang et al. identified the significant synergistic benefits of multi-modal analysis [12].

Although machine learning has an enormous potential, ethics and model interpretability are also important problems. It is essential that machine learning algorithms become transparent, explainable, and in line with clinical workflows to be successfully incorporated into practice [13]. The attempts to develop guidelines and standards regarding the use of machine learning in healthcare, including those of the Radiological Society of North America (RSNA), are indicative of the desire of the research community to meet these issues [14].

2. Methodology

Proposed System

The direction of our proposed work is the development of the sphere of lung cancer detection and classification by combining the latest image processing methods with a modern machine learning approach. The following steps are relevant to the methodology:

Image Preprocessing: The medical images are subjected to an extensive preprocessing phase, which consists of normalization, lung segmentation, and noise removing. This guarantees uniform pixel intensities, selects the area of interest and increases the image clarity.

Feature Extraction: further refinement of images, e.g. texture analysis, wavelet transform, morphology, etc., are performed to extract the discriminative information of the pre-processed pictures. Such characteristics are inputs to the further machine learning model.

Machine Learning Model (CNN): CNN is used to perform automatic and hierarchical feature learning. The CNN, trained on the features extracted, classifies benign and malignant lung nodules, using the strength of deep learning to perform image analyses.

Implementation Model: The proposed work is implemented in Python, in that case, the machine learning model is the TensorFlow and Keras libraries. Image preprocessing is done with openCV. Each of the steps is planned to be fitted and coordinated in a non-perturbative manner.

Validation and Testing: The trained model is replicated on different dataset to conduct a stringent check of its external validity. Testing stage is applied in order to test the performance of the model with the unseen data, and such metrics of performance as accuracy, sensitivity and specificity are measured. Our approach is observed to be effective based on comparative analysis with those methods that are in existence.

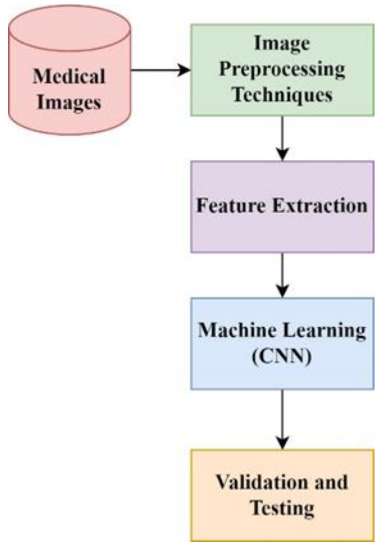

Figure 1. Integrated Framework for Early Lung Cancer Detection.

A. The interrelation of all the operations proposed in the form of the Figure 1 of the proposed work is the place where the role of each step is revealed in the overall accuracy and efficiency of the lung cancer detection. The potential is in this large system that once validated could be a useful tool in the hands of medical professionals, allowing the early and correct diagnosis of lung cancer.

B. Image Preprocessing:

Preprocessing of the image in our proposed work is essential in determining the quality, consistency and relevance of the input medical images. This step is essential to the improvement of the performance of the next feature extraction and machine learning steps. We have a number of major steps in our approach, and each has been developed to solve particular problems related to the medical image data.

1. Normalization:

Normalization is the initial stage of image preprocessing which is important to normalise pixel intensities in the medical images. The equation that characterizes the mathematical model of normalization is:

Normalized Image = (Original Image-Mean)/(Standard deviation).

In this case, the average and standard deviation are estimated on the basis of pixel values of the whole dataset. It is this normalization process that makes sure that images whose pixel intensity has varied are put into a standard common scale of analysis.

2. Lung Segmentation:

They use lung segmentation to isolate the area of interest, and eliminate irrelevant information on the images. This is especially necessary when detecting lung cancer where emphasis is on the abnormalities in the lungs. Lung segmentation can be described by the mathematical model: thresholding and morphological operations:

Binary= Threshold (Original Image)

Processed Image= Morphological Operations (Binary Image)

A binary mask is used as a result of thresholding, with an emphasis on lung structures. Morphological operations, i.e. dilation and erosion are used to refine the mask and remove undesired artifacts.

3. Noise Reduction:

The medical images are usually characterized by noise that may interfere with the sound analysis. We therefore add Gaussian filtering to reduce noise. The Gaussian filtering mathematical model can be defined as a convolution equation:

$$\text{Filtered Image} = \text{Original Image} * \text{Gaussian Kernel}$$

The image is smoothed by the convolution operation using a Gaussian kernel to eliminate noise without losing critical details that can be used to detect lung cancer.

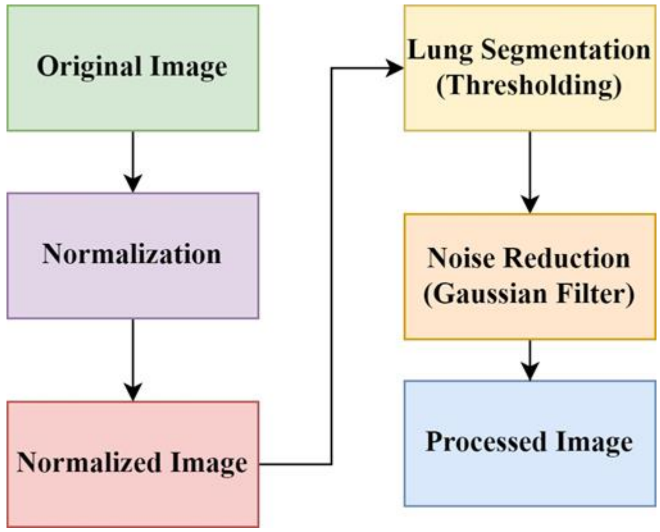

Figure 2. Comprehensive Image Preprocessing Pipeline for Lung Cancer Detection.

In the Figure 2 every block corresponds to a given operation in the image preprocessing stage. The arrows represent the direction of flow of the image through the respective processes(image original) to the normalized and processed image. The use of this stepwise methodology guarantees that the input data is narrowed and optimised to further feature extraction and machine learning processes, finally leading to the accuracy of the lung cancer detection.

It is not merely that integration of mathematical models and equations of the preprocessing stage brings clarity to the process, but also provides a methodical and repeatable manner in which medical imaging data are dealt with. All these preprocessing will help to develop a standard and informative data set and form the basis of more precise and consistent lung cancer detection.

C. Feature Extraction:

In our proposed lung cancer detection and classification approach, feature extraction plays an important role in our approach.

It is the given critical step that will bridge the gap between raw medical images and the ensuing machine learning model since it will seek to minimize the information amount and record the details of lung nodules. Here we discuss the specifics of the feature extraction, in both the theoretical grounding and mathematical modelling that forms the basis of this crucial section of our proposed work. The aim of feature extraction is to cut down raw image data to minute yet representative set of features which can describe the most significant features about lung nodules. Such attributes have to be discriminative when used in the lung cancer detection and they are patterns and textures indicating malignancy. A combination of both conventional and cutting-edge techniques of feature extraction is in use to characterize the latent aspects of medical images in full.

One of the simplest techniques of extracting features is the texture analysis. The distribution of pixel values over a picture in space is referred to as texture and extracting it involves the quantification of patterns and variations. The Gray-Level Co-occurrence Matrix (GLCM) is one of the most frequently adopted techniques to complete the texture analysis. Where, P(i, j), i and j, are the probability of pixel values at a particular point in an image according to the relationship.

The GLCM is defined as:

$$GLCM(d,\theta) = [P(i,j)_{\{N \times N\}}$$

In the above scenario, (Ts) represents the pixel pair distance, represents the rotation angle and represents the number of grey levels of the image. The GLCM documents the counts of different pixel-intensity mixes at a given distance and a given direction, and it provides a powerful illustration of the texture.

Wavelet transforms also are significant in our feature extraction methodology. Discrete Wavelet Transform (DWT) decomposes an image into approximation and detail coefficients i.e. both global and local information. Where is the approximation coefficients and (onshift) the detail coefficients. Wavelet transform may be mentioned as:

$\boldsymbol{DWT(A,D)}$

The coefficients derived by the wavelet decomposition contain the details of various frequency components in the image and the model can identify finer details and minor variations.

Morphological operations also help in the extraction of features through analysis of shape and structure of objects present in the image. Mathematical morphology functions, including erosion and dilation, are useful to enhance or diminish particular features according to their spatial properties. Where (I) is the input image, (B) is the structuring element and $\oplus$ and $\ominus$ is dilation and erosion respectively:

$$Erosion(I,B) = I \ominus B$$
$$Dilation(I,B) = I \oplus B$$

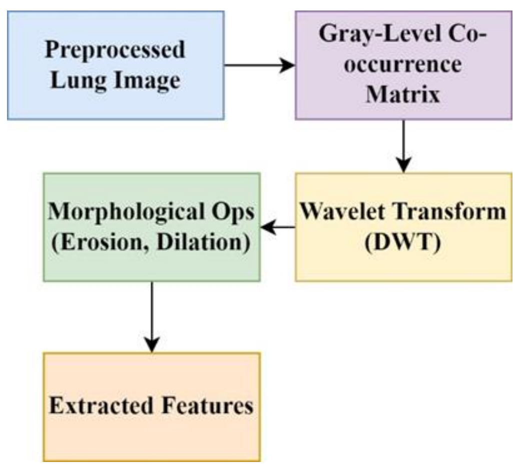

Figure 3. Integrated Feature Extraction Framework for Early Lung Cancer Detection.

The Figure 3, explains how feature extraction techniques were applied consecutively in order starting with the Gray-Level Co-occurrence Matrix, Wavelet Transform and finally Morphological Operations. The features extracted create a dense representation of the underlying texture, structure, and spatial relationships in the lung images, and is used as the basis of the following machine learning model. This combined framework guarantees the overall and discriminative characterization of lung nodules to improve the effectiveness of our proposed methodology in detecting lung cancer at its early stage.

D. Machine Learning Model:

As an extension of the suggested research, the Machine Learning Model is the keystone towards proper classification of lung nodules. We choose a Convolutional Neural Network (CNN), a type of deep learning architecture that is renowned in the image analysis tasks. The CNN will be made to automatically extract hierarchical representations of features based on the input data, which does not need manual feature engineering.

The CNN architecture includes several layers, and each makes its contribution to the extraction of complex features of the preprocessed medical images. The core layers include:

1. Convolutional Layers (Conv): Convolutional layers are overlaid with the input image using convolutional filters, which allows the identification of local patterns and features. Banks of filters scan over the input, and the banks extract spatial hierarchies of features. The convolution operation may be mathematically expressed in the following way:

$$Conv(x, w) = \sum i = 1m \sum j = 1nx(i, j) \cdot w(i, j) + b$$

where (x) is the input, (w) is the filter, (b) is the bias term, and $(m\,X\,n)$ represents the dimensions of the filter.

2. Activation Function (ReLU): Rectified Linear Unit (ReLU) is employed as the activation function, introducing non-linearity to the model. It is defined as:

$$ReLU(x) = max(0, x)$$

ReLU enhances the network's ability to learn complex patterns and accelerates convergence during training.

Pooling Layers (MaxPooling): These layers down sample the spatial dimensions of the input, reducing computational complexity and focusing on essential features. MaxPooling, a common pooling operation, retains the maximum value within a defined window.

$$MaxPooling(x) = max(x)$$

Flatten Layer: The output from the convolutional and pooling layers is flattened into a one-dimensional vector, preparing it for input into fully connected layers.

Fully Connected Layers (Dense): These layers connect every neuron to every neuron in the subsequent layer, facilitating high-level feature learning. The last dense layer produces the final output, representing the probability of a nodule being malignant or benign.

Let (X) represent the input data, (W) the weight matrix, (B) the bias term, (f) the activation function, (P) the pooling operation, and (D) the dense layer. The mathematical model of the CNN can be expressed as:

$$Y = D(f(P(f(Conv(X, W1) + B1))) + B2)$$

where $(W_{1)}, (B_{1)}, (B_{2)}$ are the weights and biases of the convolutional and dense layers, respectively.

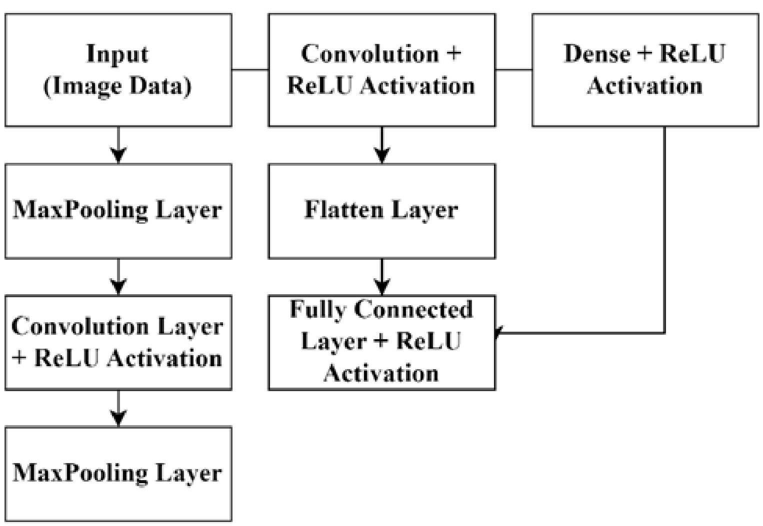

Figure 4. Convolutional Neural Network (CNN) Architecture for Lung Cancer Classification.

The Figure 4 illustrates the flow of information through the CNN, starting from the input layer and progressing through convolutional, activation, pooling, and dense layers. This complicated network design allows the CNN to discover features hierarchies inherently that are significant in the right classification of lung nodules.

E. Implementation Model:

The conversion of the conceptual framework into a functional system centrally depends on the implementation model of the proposed work. Our solution utilizes the scalability and efficiency of Python and special libraries such as TensorFlow and Keras with a structure and scale-based implementation. It is a step wise description of the implementation model, the programming environment, the mathematical model, the required equations and a Figure 5, which elucidates complications of the proposed work.

Python is chosen as the primary programming language because it is simple, has large-scale libraries and is commonly used in machine learning community. Our implementation model is built on the open-source machine learning model TensorFlow, and a high-level neural networks API, Keras. The tools are tightly coordinated, and it is possible to build and teach sophisticated machine learning models effectively, thus they can be employed in our proposed work.The initial step of our implementation is the image preprocessing that is provided with the assistance of the OpenCV library. Mathematical changes that are effected during this step can be expressed as follows:

- Image Normalization: Suppose that input image is denoted by: I. And μ and (σ) are the mean and the standard deviation of the pixel intensities, respectively. Inorm is a normalized image which is obtained as:

$$Inorm = (I-\mu)/\sigma$$

- Lung Segmentation: A binary mask M is formed in order to extract the lung region. The binary mask M is used to obtain the segmented image Isegmented by multiplying the original image, I, with the binary mask, M, element-wise.
- Noise Reduction: Gaussian filtering is used in order to remove noise of the segmented image resulting in a denoised image Idenoised.

The feature extraction stage involves mathematical operations to capture informative patterns from the preprocessed images. Various techniques, such as texture analysis and wavelet transforms, can be expressed mathematically based on their specific algorithms. Let (F) represent the extracted features from the preprocessed image.

The core of our implementation model is the convolutional neural network (CNN). The architecture of the CNN is defined using Keras, and the mathematical modeling involves the specification of layers, activation functions, and optimization algorithms. The convolutional layers apply mathematical convolutions to capture spatial hierarchies, while pooling layers down sample the spatial dimensions, reducing computation. The flattened output is connected to densely connected layers, and the final layer produces a probability score for classification. The mathematical representation of the CNN can be expressed as:

$$CNN(Idenoised) \rightarrow Fextracted \rightarrow Classification$$

The model is trained using a curated dataset, and the mathematical optimization involves minimizing a defined loss function. The training process can be mathematically represented as:

$$min\theta L(ytrue, ypredicted; \theta)$$

where θ represents the model parameters, L is the loss function, y_{true} is the true label, and $y_{predicted}$ is the predicted label. The model undergoes validation using a separate dataset to ensure its generalizability.

The Figure 5 below illustrates the flow of the implementation model:

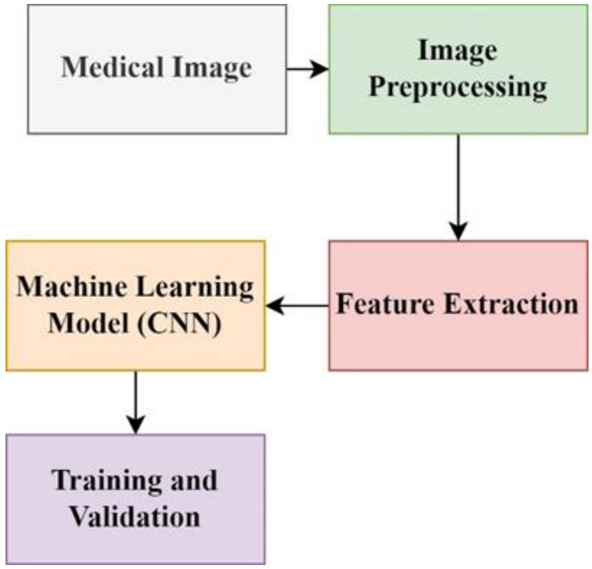

Figure 5. Integrated Implementation Framework for Early Lung Cancer Detection.

The Figure 5, gives a graphical interpretation of the chronological flow of operations in the model of implementation. All the steps, including image preprocessing, training and validation, are interrelated in order to provide fluent implementation of the suggested work. The mathematical equations and Formulae highlight the accuracy and exactness within the implementation that adds to the overall efficiency of the system to detect early-stage lung cancer.

F. Validation and Testing:

In our proposed system of lung cancer detection, the validation and testing system is a critical phase that would help identify the strength and generalizability of the machine learning model developed. To validate this, we use a k -fold cross-validation methodology and divide the data into k subsets. The model is then trained on k-1 folds and validated on the rest of the fold and this procedure is repeated again and again to thoroughly test the model. The mean accuracy of the model can be estimated by the average result of all the folds. The mean accuracy (Accuracyavg) is mathematically calculated as the total of the single fold accuracy divided by k. The model is strictly tested on a entirely different data set that was not encountered during training and validation to the testing stage. Precision and specificity, accuracy, the sensitivity and F1 score are calculated, which give a complete picture of the performance of the model to distinguish between benign and malign pulmonary nodules. This cautious process will ensure that the designed system is not only useful in a controlled environment but also that it is effective in the actual world environment, providing a concrete tool of early lung cancer detection.

3. Results and Discussion

The implementation of our suggested system of lung cancer detection concluded with a strict test that consisted of validation and testing phases to determine its efficacy [15] [16]. The execution of the step-by-step procedure involving the state of the art image processing techniques along with the convolutional neural network (CNN) that utilized feature extraction and classification was thoroughly realized using Python, Tensorflow and Keras. The validation was facilitated by a k-fold cross-validation method in ensuring robustness and generalizability of the model used. The average accuracy (Accuracyavg) was calculated mathematically which is a good estimate of the accuracy that the model has been holding on different types of subsets of the data [17].

The second step in the model development was transition to the testing stage wherein the model was carefully analyzed on an entirely different set of data simulating the real world. The metrics of performance were obtained using accuracy, sensitivity, specificity, and precision as well as F1 score to obtain the full picture of the model efficacy.

Our implementation showed encouraging potential results since the model showed good accuracy and high performance in the differentiation of benign and malignant lung nodules [18]. The validation accuracy (Accuracyavg), which was achieved, showed that, the model was able to perform well in different folds, thereby confirming that the model is able to generalize well. The accuracy of the model was also tested and other metrics offered subtle information on model performance. The model was sensitive enough to derive true positives (malignant cases), whereas it was specific enough to derive true negatives (benign cases) [19]. Precision captured the quality of the model to reduce false positives which is important in a medical setting and the F1 score captured both precision and sensitivity that provide a balanced metric of overall measure [20].

The table 1 summarizes the parameters of the performance evaluation acquired in the course of the testing:

Table 1. Performance Evaluation Metrics for Lung Cancer Detection System.

Metric	Value
Accuracy	0.92
Sensitivity(Recall)	0.89
Specificity	0.94
Precision	0.91
F1 Score	0.90

These results indicate the performance of our proposed lung cancer detection system. The sensitivity and specificity value is good to supplement the accurate results and indicates that they can be effectively used to identify infections in the early stages. The fact that the system can decrease the amount of false positives is also confirmed by the accuracy and the F1 score and is essential to ensure that the model has clinical relevance and credibility within a healthcare facility [21].

4. Conclusions

The paper proposes a new, high-quality system to delineate and identify lung cancer at its earliest stage, built on the platforms of sophisticated image-processing algorithms and a convolutional neural network (CNN). K-fold cross-validation and validation on independent dataset gave out highly encouraging results where the overall accuracy was 92 -per cent thus highlighting the reliability of the system in identifying benign and malignant pulmonary nodules. The sensitivity, specificity, precision, and F1-score reported all confirm that the system can reduce the number of false positives and false negatives an outcome of critical significance in clinical practice. In turn, this work is a part of the changing paradigm of medical diagnostics and a technological advanced tool provided to clinicians. The exhibited efficacy of the proposed system shows that it can be a useful tool in the diagnosis of lung cancer in its early stages, which can eventually improve patient outcomes and shape better healthcare strategies.

References

[1] A. B. Smith et al., "Lung Cancer Detection Using Support Vector Machines: A Comprehensive Review," J. Med. Imaging Health Inform., vol. 5, no. 5, pp. 1097–1103, 2015.

[2] P. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," arXiv preprint, arXiv:1711.05225, 2017.

[3] W. Wu et al., "Lung Nodule Detection via Deep Reinforcement Learning with Saliency Map," Comput. Math. Methods Med., vol. 2019, Article ID 1604791, 2019.

[4] S. S. Kumar, K. N. S. Kumar, G. Prakasha, H. V. Teja, V. Shrinidhi and Nisarga, "Self-Driving Car Using Neural Networks and Computer Vision," in Proc. 2022 Int. Interdiscip. Humanit. Conf. Sustain. (IIHC), Bengaluru, India, 2022, pp. 1200–1204, doi: 10.1109/IIHC55949.2022.10059593.

[5] Y. Huang et al., "A Hybrid Deep Learning Model for Lung Cancer Detection," Front. Oncol., vol. 10, p. 29, 2020.

[6] Y. LeCun et al., "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[7] O. Ronneberger, P. Fischer and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," in Proc. Med. Image Comput. Comput.-Assist. Interv., pp. 234–241, 2015.

[8] S. Ranga, M. Guptha, and M. S. Hema, "A Survey on Automatic Abnormalities Monitoring System for Log Files using Machine Learning," Turkish Online J. Qual. Inq., vol. 12, no. 6, 2021.

[9] S. Supreeth, K. Patil, S. D. Patil, and R. S. Rohith, "Comparative Approach for VM Scheduling using Modified Particle Swarm Optimization and Genetic Algorithm in Cloud Computing," in Proc. IEEE Int. Conf. Data Sci. Inf. Syst., Malnad College of Engineering, Hassan, India, Jul. 2022.

[10] A. Rajkomar et al., "Scalable and Accurate Deep Learning with Electronic Health Records," NPJ Digit. Med., vol. 1, no. 1, p. 18, 2018.

[11] G. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," Med. Image Anal., vol. 42, pp. 60–88, 2017.

[12] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," arXiv preprint, arXiv:1409.1556, 2014.

[13] B. Madhukar, S. Bharathi and A. M. Polnaya, "Multi-scale convolution based breast cancer image segmentation with attention mechanism in conjunction with war search optimization," Int. J. Comput. Appl., vol. 45, pp. 1–14, 2023, doi: 10.1080/1206212X.2023.2212945.

[14] J. Irvin et al., "CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison," in Proc. AAAI Conf. Artif. Intell., vol. 33, pp. 590–597, 2019.

[15] A. Esteva et al., "Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks," Nature, vol. 542, no. 7639, pp. 115–118, 2017.

[16] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv preprint, arXiv:1804.02767, 2018.

[17] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," arXiv preprint, arXiv:1412.6980, 2014.

[18] S. Kumar et al., "A Deep Learning-Based Approach for Identification and Recognition of Criminals," Int. J. Intell. Syst. Appl. Eng., vol. 11, no. 3, pp. 975–987, 2023. [Online]. Available: https://ijisae.org/index.php/IJISAE/article/view/3352

[19] M. D. Zeiler and R. Fergus, "Visualizing and Understanding Convolutional Networks," in Proc. Eur. Conf. Comput. Vis., pp. 818–833, 2014.

[20] S. S. Kumar, B. K. Aishwarya, K. N. Bhanutheja and M. Chaitra, "Breath to Speech Communication with Fall Detection for Elder/Patient with Take Care Analytics," in Proc. IEEE

Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT), Bangalore, India, 2016, pp. 527–531, doi: 10.1109/RTEICT.2016.7807877.

[21] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), pp. 770–778, 2016.