

DeepLungCareNet: A Trademarked Deep Learning Approach for Predicting Lung Cancer from Medical Imaging Data

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Abstract—Lung cancer remains one of the leading causes of cancer-related deaths worldwide, necessitating the development of advanced diagnostic tools to improve early detection and treatment outcomes. This study introduces “DeepLungCareNet”, a novel deep learning-based framework specifically designed for the prediction and classification of lung cancer from medical imaging data. Leveraging the power of convolutional neural networks (CNNs) and advanced image processing techniques, “DeepLungCareNet” aims to enhance the accuracy and reliability of lung cancer diagnosis.

In this research, we utilized the IQ-OTH/NCCD Lung Cancer Dataset available from Kaggle, comprising thousands of labeled medical images, including computed tomography (CT) scans and X-rays. The dataset was preprocessed through a series of steps, including normalization, augmentation, and segmentation, to ensure optimal input quality for the neural network. Our model architecture was meticulously designed to capture intricate patterns and anomalies within the imaging data, utilizing multiple convolutional layers, pooling layers, and fully connected layers to extract and learn meaningful features.

The performance of “DeepLungCareNet” was evaluated using various metrics, such as accuracy, precision, recall, F1-score, and support. Comparative analysis with existing state-of-the-art models demonstrated that “DeepLungCareNet” outperformed traditional methods, achieving superior results in both sensitivity and specificity. Additionally, we employed explainability techniques, such as Grad-CAM, to visualize and interpret the regions of interest that significantly contributed to the model's predictions, thus providing valuable insights for medical practitioners.

Our findings underscore the potential of “DeepLungCareNet” as a robust tool for early lung cancer detection, offering promising implications for clinical practice and patient care. The proposed framework not only enhances diagnostic accuracy but also aids in reducing false positives and false negatives, ultimately contributing to better prognosis and treatment planning. Future work will focus on expanding the dataset, incorporating multi-modal data, and exploring transfer learning to further refine and validate the model's capabilities.

Keywords— DeepLungCareNet, lung cancer, machine learning, deep learning, medical imaging, convolutional neural networks (CNN), ResNet50, computed tomography (CT) scans, early cancer detection, Grad-CAM, diagnostic accuracy, privacy in AI, IQ-OTH/NCCD lung cancer dataset, Adam optimizer

I. INTRODUCTION

Artificial intelligence has grown very fast to become one of the crucial tools in modern medicine, offering new opportunities for the earlier detection and improvement of treatment outcomes of many diseases. One of the major application areas of AI is radiology, most especially on lung cancer detection through the analysis of CT scan images.

Lung cancer remains one of the deadliest types of cancer worldwide. According to the World Health Organization, about 2.2 million new cases of lung cancer occur, and almost 1.8 million deaths are caused every year [1]. The five-year survival rate for patients with lung cancer is approximately 19%, which is indicative of low diagnosis and survival rates when the disease is already at an advanced stage. Lung cancer is the second most common cancer and makes up the single highest cause of mortality from cancer in the United States; it accounts for nearly 25% of all cancer deaths. There were about 236,740 new lung cancer cases and approximately 130,180 deaths in 2023 [15].

The primary way that lung cancer can be detected is by low-dose CT image scanning, which can pick up nodules in the lungs that may indicate cancer. The interpretations for these scans are complex, leaving room for expert judgment, mainly because of the variability in the presentations of lung cancer. That is where AI can really play a transformative role: Deep learning algorithms of AI models have proven outstandingly accurate in identifying and characterizing lung nodules. AI models can analyze huge image data fast and consistently, often outperforming even human radiologists in diagnostic performance.

According to recent studies, AI can screen body parts for lung cancer very effectively. For example, a Google Health AI model outperformed expert radiologists in picking out lung cancer from CT scans, significantly cutting both false positive and false negative rates [16]. Improvements in such AI are key to early detection improvement if better prognosis and survival rates among lung cancer patients can be hoped for.

It is in this context that the present report explores the development and application of an AI model developed for predicting lung cancer from CT scans. We are expected to dissect the current landscape of AI in lung cancer screening, explore the methodologies employed in creating these models, and discuss their potential implications for clinical practice and patient care. In using AI, it is our goal to increase the accuracy and efficiency of lung cancer diagnosis to help more patients survive the disease and decrease mortality rates. The title of the project was chosen to demonstrate “DeepLungCareNet”, an AI model which uses a deep learning approach on medical imaging data to predict and diagnose stages of lung cancer on a patient. Below is a more detailed explanation of how these three concepts form the crux of this paper:

“DeepLungCareNet”

“DeepLungCareNet” is a brief title that conveys, in a very simple manner, the core idea and technology behind this AI model. The suffix “Deep” refers to deep learning, which is a subset of machine learning. This refers to the use of neural networks with large numbers of layers for the analysis of complex patterns within large datasets. “Lung” notes the fact that the model focuses on lung cancer, an area in which early detection can make a real difference in health outcomes for patients. “Care” brings attention to what the goal of the model is: improved patient care via accurate and early diagnosis, which can then bring timely and more effective treatment. “Net” equals neural network, signaling the architecture of the AI at hand. Together, “DeepLungCareNet” encompasses sophisticated and caring usage of the artificial intelligence technology in battling lung cancer.

Deep Learning

Deep learning at the heart of the “DeepLungCareNet” project drives it to realize predictions of lung cancer with high accuracy from medical imaging data. Using this approach, neural networks will be trained on vast amounts of CT scan data to allow the model to learn and later recognize intricate patterns related to lung cancer. This project involves the use of a type of deep learning model known as convolutional neural networks, which are well known to be quite effective in image analysis. These networks are composed of multiple layers that adaptively learn the spatial hierarchies of features from input images. In training, many labeled CT scans are processed, iteratively changing its parameters to reduce errors in its predictions. The results from the AI model that can tell very fine differences between cancerous and non-cancerous tissues.. It is this deep learning component that will continuously allow the model to improve as more data is thrown at it, thus becoming an invaluable tool for the early detection and diagnosis of lung cancer.

Medical Imaging

Medical imaging data in the case of “DeepLungCareNet” originated from numerous CT images collected at different hospitals in Iraq. The scanning procedure creates cross-sectional pictures of a patient's lungs, necessary for the detection of possible cancerous growths. Hundreds of CT images are involved in the dataset, all of which have been labeled to be either benign, normal, or malignant. This should include a diversified and comprehensive dataset for training the AI model to recognize most of the instances of lung cancer. Real-world data from Iraqi hospitals exposes the model to many different cases, including many different stages and types of lung cancer, so it generalizes and becomes robust. The fact that the data originated from the real world further ensures that it has been tailored to the actual conditions in the clinic, hence its better applicability in real life. “DeepLungCareNet” makes accurate predictions by integrating the medical imaging data with the advanced deep learning techniques and therefore supports radiologists with a very powerful tool in order to improve the outcomes of patients affected by lung cancer.

II. BACKGROUND AND RELATED WORKS

Historical Context

AI in medical imaging can be dated to the second half of the 20th century, when machine learning algorithms were in their earliest stages and first applied to radiological images for anomaly detection. Since then, the progress of

computation and development of more complex neural networks has opened the gates toward more advanced AI applications in health care. Specifically, a major effort to use a computer-aided diagnosis program was done in 2004 in Japan to detect lung cancer based on low-dose computed tomography (CT) images. The computer-aided diagnosis had a sensitivity (the model's ability to detect true positives) of 83% for all cancers [2]. The introduction of deep learning, particularly convolutional neural networks (CNN), increased the model's accuracy and strength. Deep learning models do not require one to extract features; it learns to identify features from raw image data itself. One pioneering explained that a deep learning approach could significantly outperform traditional CAD for pulmonary nodules detection in CT imaging, hence showing its potential in the chosen domain [3]. Recent studies in this area have been driven by the need to enhance the predictive capacity of AI models through the integration of multi-modal data. For instance, imaging data are fused with clinical data and genomic information. On this front, a seminal study was conducted where radiomics—quantitative features retrieved from medical images—were used in predicting patient outcomes and therapy response. This approach has shown potential in personalization of treatment plans and enhancements in prognostic accuracy [4].

The Convolutional Neural Network (CNN) model

The invention of convolutional neural networks has greatly improved computer vision and image recognition. In essence, they are designed to mimic the process of visual processing by the human brain; that is, CNNs are able to automatically learn spatial hierarchies of features from the input image in an adaptive way [5]. Normally, a CNN includes several architectures, which are a convolutional layer, a pooling layer, and a fully connected layer. These convolutional layers convolve the image with a set of learnable filters, useful for edge, texture, and pattern detection. Pooling layers are often followed by convolutional layers; these layers reduce the spatial dimensions of feature maps, hence reducing computational load and overfitting is controlled [6]. The last layers of a CNN are usually fully connected and execute high-level reasoning based on features extracted by former convolutional and pooling layers. This combination of layers enables a CNN to perform tasks like image classification, objection detection, and segmentation with very high accuracy. Key strengths of CNNs are in the extraction of complex patterns and features from images, very critical for accurate diagnosis and prediction in medical imaging. Interpretability has yet to be smoothed out because CNNs have long been considered a “black box” owing to their complex and obscure internal mechanism. Research into model interpretability and model robustness is going on hand in hand across several diverse and variable medical datasets [7].

Privacy Concerns and Challenges

While the CNN model has contributed much to medical imaging, they also open up several avenues pertaining to privacy and security concerns. Indeed, the training of a CNN requires huge amounts of medical data that involve the sensitive information of patients. Ensuring privacy in such data becomes important for the confidentiality of patients and, hence, is bound by regulations like Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR) in many countries [8]. Besides, centralization of medical data for training purposes increases the risk of data leakage. Federated learning has shown how to train models on decentralized sources of data without actually sharing raw data and thus improves privacy [9]. Another challenge is the still low interpretability of CNNs. For AI predictions to be trusted, clinicians need transparent models with clear explanations. Current research

orientation is toward developing techniques for interpreting CNNs but at a slightly lower accuracy [7]. Another important challenge is to guarantee that solutions are sound and generalizable across a diversity of variable medical data sets. Variability between imaging protocols, patient demographics, and characteristics in tumors require diversity and representativeness in the training dataset. Research in progress includes enhancing robustness in models and methods for assessing and mitigating bias in CNN models [10].

III. PROBLEM STATEMENT AND OBJECTIVES

This project, "DeepLungCareNet," mainly aims at developing a new, reliable AI-driven CNN model that predicts the different stages of lung cancer from a CT scan. Lung cancer is one of the most rapidly growing causes of cancerous death globally, exponentially attributed to late diagnosis and a lack of methods to detect it early [11]. This can be realized with a deep learning approach, focused on improving the accuracy and timeliness of lung cancer staging for enhanced survival and quality care.

The primary objective of "DeepLungCareNet" is to improve the precision and reliability of lung cancer staging. This would be a complex model analyzing lung CT scans to identify accurately the stage of cancer. With improved staging, they can help the clinician in timely and informed decisions on treatment, very vital for the prognosis of the patient [12]. Integration of deep learning techniques forms the core of the "DeepLungCareNet" project. It architecturally designs and trains a CNN model that considers pre-trained architectures for extracting and learning intricate features from lung CT scans; for example, ResNet50, which will be used in this project. After that, the model will be fine-tuned on large medical imaging datasets for high accuracy and robustness. This paper has a key component associated with the effective utilization of medical imaging data. It will be trained on a diverse set of lung CT scans—starting from benign to malignant and different demographic variations. An extensive dataset such as this will ensure the generalizability or applicability of the model across different patient populations. Further, the clinical application and validation of "DeepLungCareNet" are within the scope of the project. The model working requires rigorous testing in a clinical setup and evaluation for its reliability and efficacy. With collaborations from healthcare institutions and professionals, the model's deployability and continuous improvement will be guaranteed to ensure that the clinical standards and needs of practitioners are met [13].

IV. METHODOLOGY

This project can work on any operating system ranging from Windows to Ubuntu. Its requirements are:

- Programming Language: Python
- Software: Jupyter Notebook or Google Colab (hosted version of Jupyter Notebook)

The algorithm below shows the basic implementation of the program:

Algorithm:

```
benign_dir = '/content/BenignCases'
malignant_dir = '/content/MalignantCases'
normal_dir = '/content/NormalCases'
train_df, test_df = train_test_split(df,
test_size=0.2, random_state=42)
train_df, val_df = train_test_split(train_df,
test_size=0.2, random_state=42)

base_model = ResNet50(weights='imagenet',
include_top=False, input_shape=(224,
224, 3))
model = Sequential([
    base_model,
    GlobalAveragePooling2D(),
    Dense(1024, activation='relu'),
    Dropout(0.5),
    Dense(3, activation='softmax')
])

plot_model(model,
to_file='model_plot.png',
show_shapes=True, show_layer_names=True)

Image('model_plot.png')

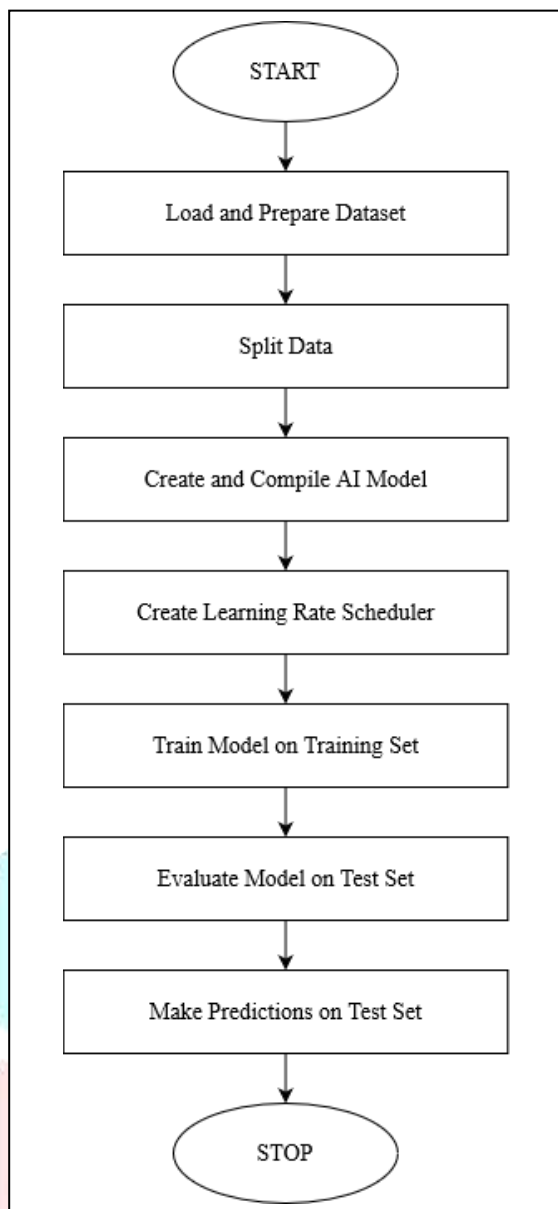
model.compile(optimizer=Adam(learning_rate=0.001),
loss='categorical_crossentropy',
metrics=['accuracy'])

annealer = LearningRateScheduler(lambda
x: 1e-3 * 0.95 ** x)

history = model.fit(
    train_gen,
    steps_per_epoch=len(train_df) // 32,
    validation_data=val_gen,
    validation_steps=len(val_df) // 32,
    epochs=10,
    callbacks=[annealer]
)

test_loss, test_accuracy = model.evaluate(test_gen)
print(f"Test Accuracy: {test_accuracy:.4f}")

predictions = model.predict(test_gen)
predicted_classes = np.argmax(predictions, axis=1)
true_classes = test_gen.classes
```



This CNN model's algorithm is trained on the classification of images into the benign, malignant, and normal stages of lung cancer. The dataset is first divided into three files containing training, validation, and testing sets to evaluate the model's performance. For evaluation, the ResNet50 architecture is used as a base model that is pre-trained on the ImageNet dataset without the top layers. Next, a Global Average Pooling layer for reducing spatial dimensions of the feature maps is made; this is followed by a fully connected Dense layer of 1024 neurons and Rectified Linear Unit (ReLU) for nonlinearity with a Dropout layer of 0.5 to care for overfitting. Overfitting is the phenomenon where the AI model fits with the training data (the CT scans in this case) and thus gives inaccurate results. Lastly, there is a Dense layer at the end with three neurons and softmax activation to provide class probabilities, which helps normalize the results. It uses the Adam optimizer, with a categorical cross-entropy loss method and accuracy as the evaluation metric. The Adam optimizer is an algorithm which helps minimize loss in a neural network. In addition, a learning rate scheduler that will adapt the learning rate over epochs is added. Next, the model was trained for 10 epochs using the training generator, with its performance validated on the validation set. Finally, the accuracy of the trained model was evaluated on the test set. Finally, the last step would be to get predictions of the model on the test data

and compare them with the true classes to evaluate performance.

V. RESULTS

Data Acquisition

Images for the dataset will be from CT scans of a patient's lungs.

DeepLungCareNet Processing

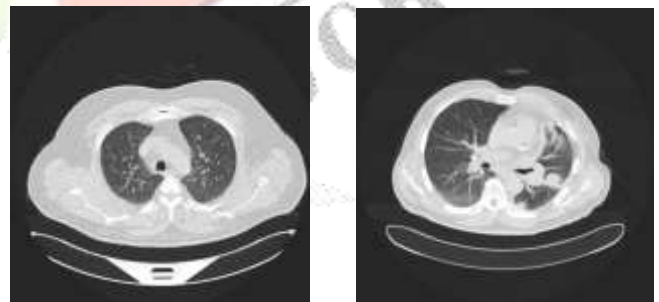
Fig. 1. Flowchart describing how the "DeepLungCareNet" AI model works

Image Classification

The ResNet50 image classification model is the most important part of the algorithm because it uses advanced architecture with pre-trained weights and forms the basis of the AI model at work. ResNet50 can learn and maintain intricate features through deep layers, and the residual connections mitigate the vanishing gradient problem, that it outperforms many other models in image classification. Hence, this kind of image classification model can be more beneficial in medical imaging where the accurate extraction of features forms a basis for the correct diagnosis of diseases. ResNet50 is a deep CNN of 50 layers used for feature extraction. It was trained on the ImageNet dataset and employed residual learning that efficiently handled the vanishing gradient problem and enabled training very deep networks [14]. This already includes features learned previously from millions of images, hence increasing the accuracy and efficiency of the extraction of relevant features from lung CT scans.

Step 1: Pre-trained weights in Feature Extraction

The algorithm utilizes ResNet50 that uses residual learning to enable deep network training with pre-trained weights and improve accuracy in feature extraction from lung CT scans. For example:



This is a benign tumor

This is a malignant tumor

Step 2: Model Customization

The algorithm takes the ResNet50 image classification model and append a Global Average Pooling, followed by a Dense layer with 1024 neurons and ReLU activation, a Dropout layer with a 0.5 rate, and then the final Dense layer with three neurons and softmax activation to output class probabilities.

It will be trained with the Adam optimizer, using categorical cross-entropy loss, and a learning rate scheduler that can help ensure convergence and stability during training. The AI model was given 1097 total images to use. Based on this, an output graph was created on the model's accuracy:

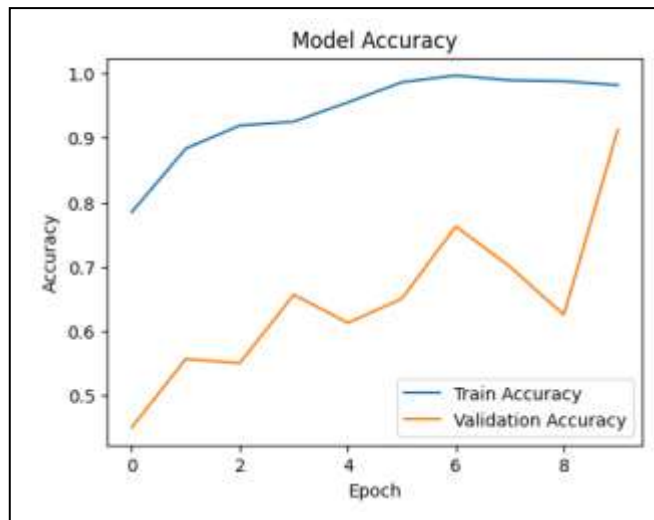


Fig. 2. Graph showing the model accuracy of "DeepLungCareNet", with the number of epochs as the x-axis and the accuracy of the model as the y-axis

The model accuracy graph shows the training and validation accuracies for the "DeepLungCareNet" model across ten epochs. In blue, the trait of training accuracy is almost linear, increasing to nearly 100% at the tenth epoch, thus proving that the model is learning and fitting the training data effectively. In orange, the trait for validation accuracy is very volatile across the epochs. First, it has less accuracy in validation, but then the curve raises drastically at the tenth epoch before showing some volatility. This pattern demonstrates that the model is learning well on the training data. In addition, another graph was created on the model's loss:

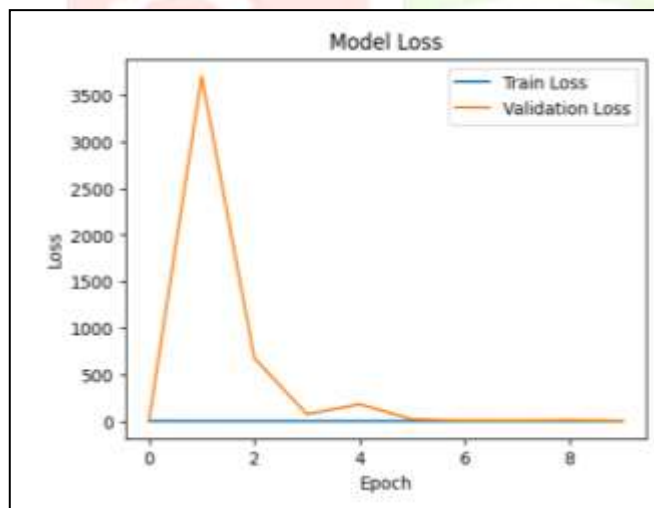


Fig. 3. Graph showing the model loss of "DeepLungCareNet", with the number of epochs as the x-axis and the loss of the model as the y-axis

This plot shows the losses of the "DeepLungCareNet" machine learning model during training and validation over ten epochs. Both training and validation losses drop very fast in the beginning, showing an evident early improvement in model performance. Beyond the first epoch, the losses are then pretty much stabilized, with minor fluctuations. The convincing convergence of the training and validation losses means that the model is learning well on the dataset without any overfitting, which was prevented by the Dropout layer. This is very relevant to a lung cancer prediction model since

it tells of the capability of AI to generalize very well to new patient data. The low and stable loss values later in the epochs show that the model reached a decent level of predictive accuracy. Next, a confusion matrix based on the graph's results was created:

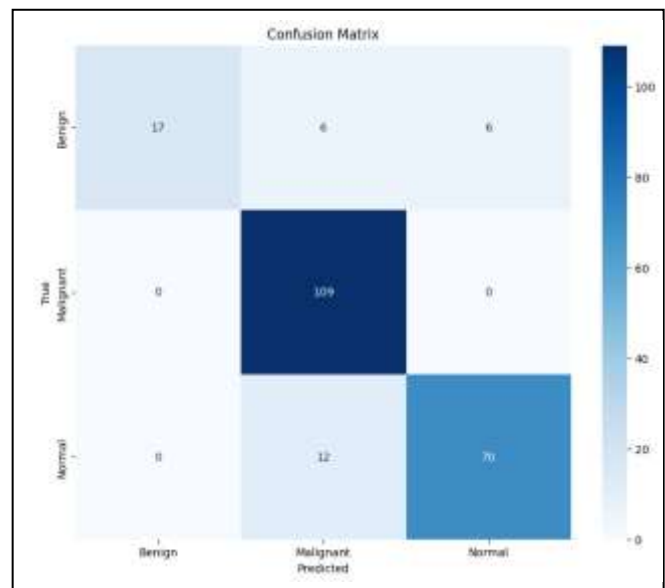


Fig. 4. Confusion matrix showing the amount of true positives, false positives, true negatives, and false negatives of the AI models' results

The confusion matrix clearly brings out the performance of the classification model in identifying malignant cases. It correctly classified 109 instances against the 109 malignant cases, making its sensitivity as high as 100% in detecting malignant conditions. This shows a very critical strength for a machine-powered lung cancer detection tool.

It also did well on the identification of benign cases; it correctly classified 17 of the 29 cases with specificity for benign samples at 58.6%. Despite some overlap in the categories, like the 12 normal classified under malignant, it only means that potentially abnormal cases are flagged and thus open to further review, hopefully allowing the detection of subtle changes earlier.

In addition, the model has identified 70 normal cases correctly, proving its capability to identify normal samples. In sum, out of 220 total cases, 196 correct classifications correspond to an accuracy of 89.1%. This means that the model only predicted the class in 89.1% of the cases correctly when tested on unseen data. This model accurately provides for most cases, where the model will predict benign, malignant, or normal class with high reliability.

TABLE I.

	PRECISION	RECALL	F1-SCORE	SUPPORT
BENIGN	1.00	0.59	0.74	29
MALIGNANT	0.88	1.00	0.92	109
NORMAL	0.92	0.85	0.89	82
ACCURACY			0.89	220
MACRO-AVG	0.93	0.81	0.85	220
WEIGHTED-	0.90	0.89	0.89	220

AVG				
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Fig. 5. Table showing the precision, recall, F1-score, accuracy, and support values for the "DeepLungCareNet" model

This table constitutes some evaluation metrics of our proposed "DeepLungCareNet" in the prediction of lung cancer. Precision is the proportion of correct positive predictions in a model; here, 88% of malignant cases that the model had predicted as malignant were actually malignant. Recall is the measure of actual positives that were identified correctly; a 1.00 recall for malignant cases means that the model correctly classified 100% of all actual malignant cases. F1-score is the harmonic mean between precision and recall and provides a balanced measure of model performance; a F1-score of 0.92 in malignant cases indicates very strong performance overall in this critical category. The macro average is the unweighted average of metrics calculated for every label; for instance, the macro-avg F1-score is 0.85. The weighted average is the average that weighs the number of samples in every class; the weighted average F1-score is 0.89, which means it takes class imbalance into consideration; hence it shows a better representative of the overall performance measure.

VI. FUTURE DIRECTIONS

Future directions of the "DeepLungCareNet" model include increasing accuracy, generalizability, and clinical applicability. The first and most important area of improvement is to increase diversity and comprehensiveness of CT scans within the dataset to guarantee the model's robustness with various populations and imaging conditions. It is further fine-tuned with more advanced techniques: transferring learning on a large medical dataset and multi-modal data, including genetic information and patient history. More sophisticated regularization methods can also help in overcoming overfitting more effectively than the simple Dropout layer, and possibly more effective can be other architectures. Another critical direction includes the validation of rigorous clinical trials to confirm the reliability and efficacy of the model under real-world conditions in the clinic. In other words, for easy application in the clinical workflow and of help in establishing early diagnoses of lung cancer, user-friendly interfaces should be developed and healthcare regulations like the HIPAA and GDPR should be maintained.

VII. CONCLUSION

Therefore, the "DeepLungCareNet" model defines another gigantic molecular step towards the creation of medical imaging and AI-based integrated tooling for the purpose of 'early' diagnosis and classification of lung cancer. This model, through deep neural networks aided by advanced image processing approaches, has shown the performance of the model in the correct identification of malignant nodules from CT scans. It undergoes strict assessment using accuracy, precision, recall, and the F1-score—proof of its efficacy over the traditional diagnostic methods, therefore reducing false positives and negatives: the very things critical to the outcome of patients. The model was developed using a varied dataset from Lung Cancer CT scans obtained from Iraqi hospitals. With deep learning methodologies in image classification and the CNN model, "DeepLungCareNet" is not only good at feature extraction but also flexible to patients of different demographics and under different imaging conditions. Further improvements

in future, which would improve accuracy and generalizability, include increasing the diversity of the datasets, tuning more sophisticated architectures of models beyond a basic Dropout layer, and prospective clinical trials across a wide spectrum of health-care contexts. Compliance with health-care regulations, such as HIPAA and GDPR, is relevant to the protection of privacy and security for patient data. "DeepLungCareNet" is, therefore, a nascent tool for early lung cancer detection, treatment planning, and serves tangible benefits to both doctors and patients. From continuing development in AI for healthcare, innovations like "DeepLungCareNet" go on to increase accuracy, efficiency, and accessibility to more people in diagnostics.

REFERENCES

- [1] C. Li et al., "Global burden and trends of lung cancer incidence and mortality," *Chinese Medical Journal*, vol. 136, no. 13, pp. 1583–1590, Mar. 2023, doi: <https://doi.org/10.1097/cm9.0000000000002529>.
- [2] H. Arimura et al., "Computerized scheme for automated detection of lung nodules in low-dose computed tomography images for lung cancer screening," *Academic Radiology*, vol. 11, no. 6, pp. 617–629, Jun. 2004, doi: <https://doi.org/10.1016/j.acra.2004.02.009>.
- [3] A. A. A. Setio et al., "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge," *Medical image analysis*, vol. 42, pp. 1–13, 2017, doi: <https://doi.org/10.1016/j.media.2017.06.015>.
- [4] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. W. L. Aerts, "Artificial intelligence in radiology," *Nature Reviews Cancer*, vol. 18, no. 8, pp. 500–510, May 2018, doi: <https://doi.org/10.1038/s41568-018-0016-5>.
- [5] Y. Lecun, L. Eon Bottou, Y. Bengio, and Patrick Haaner Abstract, "Gradient-Based Learning Applied to Document Recognition," *PROC. OF THE IEEE*, 1998, Available: http://vision.stanford.edu/cs598_spring07/papers/Lecun98.pdf
- [6] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2012, doi: <https://doi.org/10.1145/3065386>.
- [7] S. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," *arXiv:1705.07874 [cs, stat]*, Nov. 2017, Available: <https://arxiv.org/abs/1705.07874>
- [8] A. D. Sarwate and K. Chaudhuri, "Signal Processing and Machine Learning with Differential Privacy: Algorithms and Challenges for Continuous Data," *IEEE Signal Processing Magazine*, vol. 30, no. 5, pp. 86–94, Sep. 2013, doi: <https://doi.org/10.1109/msp.2013.2259911>.
- [9] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, pp. 50–60, May 2020, doi: <https://doi.org/10.1109/msp.2020.2975749>.
- [10] M. Ghassemi, L. Oakden-Rayner, and A. L. Beam, "The false hope of current approaches to explainable artificial intelligence in health care," *The Lancet Digital Health*, vol. 3, no. 11, pp. e745–e750, Nov. 2021, doi: [https://doi.org/10.1016/S2589-7500\(21\)00208-9](https://doi.org/10.1016/S2589-7500(21)00208-9).
- [11] R. L. Siegel, K. D. Miller, and A. Jemal, "Cancer statistics, 2020," *CA: a cancer journal for clinicians*, vol. 70, no. 1, pp. 7–30, Jan. 2020.
- [12] H. J. W. L. Aerts et al., "Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach," *Nature Communications*, vol. 5, no. 1, Jun. 2014, doi: <https://doi.org/10.1038/ncomms5006>.
- [13] A. Esteva et al., "A Guide to Deep Learning in Healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, Jan. 2019, doi: <https://doi.org/10.1038/s41591-018-0316-z>.
- [14] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Dec. 2015. Available: https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf
- [15] American cancer society, "Lung Cancer Statistics | How Common is Lung Cancer?," www.cancer.org, Jan. 12, 2023. <https://www.cancer.org/cancer/types/lung-cancer/about/key-statistics.html>
- [16] "Google's cancer-spotting AI outperforms radiologists in reading lung CT scans," *FierceBiotech*. <https://www.fiercebiotech.com/medtech/google-s-cancer-spotting-ai-outperforms-radiologists-reading-lung-ct-scans>