Enhancing Lung Cancer Diagnosis with Custom-Designed Convolutional Neural Network

P.K.P. Sandamal[1] and G.R. Perera[2]*
1Department of Software Engineering, Faculty of Computing, NSBM Green University, Sri Lanka
2Department of Computer and Data Science, Faculty of Computing, NSBM Green University, Sri Lanka
Corresponding Author E-mail: gayanp@nsbm.ac.lk

***Abstract* - Lung cancer is a major cause of cancer deaths globally, which highlights the importance of early detection to improve survival rates. This study focuses on creating and testing a custom Convolutional Neural Network (CNN) designed for accurate lung cancer detection based on Computed Tomography (CT) Scan images of the lungs. To evaluate its effectiveness, the proposed custom CNN architecture is compared with two established pre-trained models, ResNet50 and VGG16. The research utilized datasets from the Kaggle website and Teaching Hospital Anuradhapura Sri Lanka, with images which are preprocessed to a size of 256x256 pixels. Techniques such as SMOTE were employed for class balancing and data augmentation to boost model performance. The custom CNN, which includes multiple Conv2D layers, MaxPooling2D layers, dropout, and batch normalization, achieved an impressive accuracy of 98.55%. This performance surpassed that of ResNet50, which achieved 97.67%, and VGG16, which recorded 66.15%. The models were trained and evaluated using cross-validation, measuring performance through metrics like precision, recall, and F1-score. Despite the promising results, limitations exist due to reliance on a specific dataset and the necessity for further clinical validation. This research indicates that custom CNN performs better than pre-trained models in detecting lung cancer.**

Keywords - convolutional neural network, lung cancer detection, machine learning

I. Introduction

Lung cancer remains one of the deadliest forms of cancer globally [1]. At the same time, technologies such as MRI and CT scans are commonly used for identifying lung cancer, early-stage detection remains a challenging task that heavily relies on the expertise of radiologists [2]. Convolutional Neural Networks (CNNs), a type of machine learning, are gaining popularity in the analysis of medical images [3]. CNN could learn and identify patterns of images, making patterns particularly useful for tasks like cancer detection. With access to large datasets and advanced computing capabilities, CNNs can provide accurate diagnoses and serve as valuable support tools for radiologists.

The objective of this study is to examine the effectiveness of different CNN architectures for lung cancer detection. This study compares custom CNN with two well-established models, ResNet50 and VGG16. The custom CNN is designed to balance complexity and efficiency, incorporating insights from existing models and related studies to enhance accuracy.

ResNet50 employs "residual learning" to construct intense networks without compromising performance [4]. VGG16 demonstrates the advantages of using numerous small filters in a simple, consistent design [5]. These insights informed the development of the custom CNN, intending to achieve high performance in lung cancer detection.

This approach's potential impact extends to enhancing the accuracy, and by focusing on lung cancer detection, this study seeks to contribute to earlier diagnosis and improved patient outcomes.

II. Literature Review

Patel and Ganatra [6] proposed an innovative system integrating Internet of Things (IoT) and deep learning for early breast cancer detection in institutional settings. The study suggests using thermal imaging cameras combined with convolutional neural networks (CNNs) to automate breast cancer screening. The authors developed a two-factor framework for cancer detection involving initial thermal image collection and subsequent targeted scanning. The proposed system aims to improve early detection rates, particularly in underserved communities, by enabling continuous health monitoring and automated screening in institutional environments.

Bushara A. R. and Vinod Kumar R. S. [7] explore deep learning-based lung cancer classification using augmented Convolutional Neural Networks (CNNs). This study utilizes data augmentation techniques on CT images to enhance classification accuracy, specifically employing scaling, rotation, and contrast modification transformations. The Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) was used for evaluation. The proposed system demonstrated a high accuracy of 95% with precision, recall, and F1-score for benign and malignant test data around 0.93 to 0.96, showcasing significant improvements over other state-of-the-art methods. The authors emphasize the critical role of early detection in improving survival rates. Thus, their work supports the development of more efficient Computer-Aided Diagnostic (CAD) systems for early lung cancer identification, potentially saving lives by facilitating earlier treatment interventions.

Atsushi Teramoto, Tetsuya Tsukamoto, Yuka Kiriyama, and Hiroshi Fujita developed an automated classification system for differentiating lung cancer types—adenocarcinoma, squamous cell carcinoma, and small cell carcinoma—using deep convolutional neural networks (DCNNs) applied to cytological images [8]. The DCNN model, composed of three convolutional layers, three pooling layers, and two fully connected layers, processed images preprocessed to a uniform resolution of 256x256 pixels. This utilized data augmentation techniques like rotation, flipping,

and filtering to combat overfitting. The system achieved an accuracy rate of approximately 71%, comparable to the diagnostic accuracy of cytotechnologists and pathologists, demonstrating the potential of DCNNs to support and enhance the precision of lung cancer diagnosis through cytological evaluation.

Sathyakumar et al. [9] focused on evaluating the efficacy of Artificial Intelligence (AI) in the automated detection of lung cancer through Deep Convolutional Neural Networks (DCNNs). This study analyzed various AI models and compared their performance to human physicians and radiologists in detecting lung nodules. The models reviewed primarily used chest CT scans for detection, with a specific age focus of 18-65 years old, excluding any studies using PET scans, chest X-rays, or genomic data. The performance of the AI systems was gauged through metrics such as sensitivity, specificity, accuracy, ROC curve, and AUC, demonstrating the high accuracy and low false-positive rates of these advanced technologies. This narrative review emphasizes the potential of AI-assisted systems in reducing the workload of physicians, thereby mitigating the risk of burnout and improving the quality of patient care. Integrating AI in lung cancer screening enhances diagnostic accuracy and preserves the invaluable doctor-patient relationship by allowing doctors more time for direct patient interaction.

The research paper by Wadood Abdul discusses an Automatic Lung Cancer Detection and Classification (ALCDC) system utilizing a Convolutional Neural Network (CNN) to analyze CT scan images for lung cancer detection [10]. The system distinguishes between malignant and benign tumors with a reported accuracy of 97.2%, considered superior to existing systems. This study, which taps into the Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI), emphasizes the potential of deep learning techniques in medical diagnostics to improve accuracy and efficiency in lung cancer detection. The CNN model benefits from automated feature extraction that bypasses the need for hand-engineered methods, thereby enhancing the robustness and reliability of the diagnostic process.

Dewan Ziaul Karim focused on detecting lung cancer from histopathological images using a Convolution Neural Network (CNN) [11]. Their study employed a CNN model to classify three types of lung tissues: Benign tissue, Adenocarcinoma, and Squamous cell carcinoma. The model was trained with a dataset of 15,000 images, divided into training, validation, and testing groups. Notably, their CNN model achieved a training accuracy of 98.15% and a validation accuracy of 98.07%, demonstrating its high efficiency in classifying lung cancer types from histopathological images. This work highlights the potential of deep learning models to assist pathologists in diagnosing lung cancer accurately and efficiently, contributing to better patient management and treatment outcomes.

Adarsh Pradhan, Bhaskarjyoti Sarma, and Bhiman Kr Dey have developed a 3D Convolutional Neural Network (CNN) approach for detecting lung cancer from CT scans [12]. Utilizing the SPIE-AAPM Lung CT Challenge dataset, this implemented morphological preprocessing techniques to enhance the visibility of lung nodules, such as converting images to Hounsfield Units and applying lung nodule masks. Their method involves cropping, resizing, and rescaling DICOM image slices, then training a 3D CNN model. This approach yielded impressive results, with their model achieving a training accuracy of 83.33%, a testing accuracy of 100%, and perfect scores in precision, recall, kappa-score, and F-score, highlighting its potential effectiveness in lung cancer detection. Susmita Das and Swanirbhar Majumder's paper compares traditional Computer Aided Diagnosis (CAD) schemes with those based on deep learning techniques for the detection of pulmonary cancer [13]. This comparative analysis highlights that Convolutional Neural Networks (CNNs) are predominantly used due to their effectiveness in feature learning and pattern recognition within pulmonary cancer detection applications. This emphasizes the advantages of deep learning CAD systems in automatically recognizing lung nodules with high accuracy and efficiency, potentially reducing the radiologist's workload significantly. The study points out several challenges in implementing these systems, such as computational demands and the need for extensive training datasets, but also notes the superior performance of deep learning models over traditional methods. The authors conclude that deep learning enhances the diagnostic processes by handling large-scale image data more effectively, leading to better detection rates of pulmonary nodules.

Bijaya Kumar Hatuwal and Himal Chand Thapa conducted a study on lung cancer detection using Convolutional Neural Networks (CNNs) on histopathological images [14]. This research focuses on classifying histopathological images into three types: benign tissue, adenocarcinoma, and squamous cell carcinoma. The CNN model developed achieved training and validation accuracies of 96.11% and 97.2%, respectively, indicating high effectiveness in classifying lung cancer types from biopsied tissue images. This approach enhances the speed and accuracy of diagnosing lung cancer, which is crucial for early treatment and improving patient survival rates. Their study demonstrates the potential of deep learning in medical image analysis, offering a more reliable tool for pathologists and enhancing diagnostic outcomes.

Chao Zhang et al., titled "Toward an Expert Level of Lung Cancer Detection and Classification Using a Deep Convolutional Neural Network," demonstrates the use of a three-dimensional convolutional neural network (CNN) to enhance the detection and classification of pulmonary nodules from CT scans [15]. This deep learning approach was trained and validated using a large dataset from multiple clinical centers, achieving a sensitivity of 84.4% and a specificity of 83.0%. The CNN model showed superior performance over manual assessments by radiologists, suggesting its potential to significantly improve the efficiency and accuracy of lung cancer screening.

III. METHODOLOGY

A. Dataset

The dataset, gathered from Kegalle website [16], includes CT scan images divided into three categories: benign, malignant, and normal. Additionally, the dataset was gathered from the teaching hospital Anuradhapura, which was used for secondary texturing.

B. Model Architecture

According to Figure 1, a custom CNN model for lung cancer detection features an input layer accepting 256x256x1 grayscale images, followed by two convolutional layers (Conv_1 and Conv_2). Each is paired with max pooling. These layers progressively reduce spatial dimensions while extracting features.

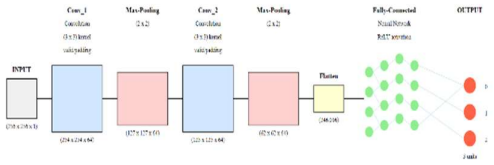

Fig. 1. Model Architecture

The flattened output of 246,016 units feeds into a fully connected layer of 16 units with ReLU activation. The model concludes with an output layer of 3 units using softmax activation to classify images such as Benign, Malignant, or Normal.

This custom cnn model has a simpler design with fewer parameters, which leads to faster training and quicker predictions. Further, it reduces the chance of overfitting, especially when using smaller datasets. Additionally, the model is specifically designed for CT scan images, allowing it to focus on important features that help tell the difference between benign, malignant, and normal cases, which can improve accuracy. Moreover, its simpler design makes it easier to understand and use in settings with limited resources, allowing faster adjustments in tuning and optimizing the model.

C. Data Preprocess

Grayscale CT scan images are loaded and resized to 256x256 pixels in the preprocessing stage. The pixel values are normalized by dividing them by 255.0 to bring them into the range of 0 to 1. Optionally, Gaussian blur is applied to reduce noise. Finally, the images are reshaped to (256, 256, 1) to prepare them for the neural network input.

D. Key Components of the Model

Input Layer: This layer sets the input shape to (256x256x1) for grayscale images, where each image has 256x256 pixels with 1 channel (grayscale). The pixel values are normalized by dividing 255.0, bringing them into the range [0, 1], which helps in faster convergence during training.

Conv_1 Layer: This layer applies 64 filters of size (3x3) to the image. Each filter detects specific patterns (such as edges or textures) in different parts of the image. The ReLU activation function is used here to introduce non-linearity, allowing the network to capture more complex features. The convolution operation slightly reduces the size from 256x256 to 254x254 due to the kernel size, while the depth becomes 64 (one channel per filter).

MaxPool Layer: This layer performs down-sampling by reducing the spatial dimensions from 254x254 to 127x127. It does this by selecting the maximum value from each (2x2) patch of the image, helping to reduce the amount of data and computation while preserving important features. The depth (64 channels) remains unchanged.

Conv_2 Layer: Like Conv_1, this layer applies 64 additional filters with a (3x3) kernel to the down-sampled image, looking for more complex patterns that combine the features from Conv_1. The ReLU activation is again used to add non-linearity. The output size is reduced to 125x125, and the image still has 64 channels.

MaxPool Layer: Like the previous MaxPooling layer, this layer further reduces the image size from 125x125 to 62x62, again retaining the strongest features while reducing computational load. The number of channels remains at 64.

Flatten Layer: This layer flattens the 3D output from the previous layer (shape (62x62x64)) into a 1D array (246,016 elements).

Fully Connected Layer: This layer has 16 neurons. It takes all 246,016 values from the flattened layer and connects them to each of these neurons. The ReLU activation function is applied here, enabling the model to capture complex relationships between the features extracted by the convolutional layers.

Output Layer: The final layer has 3 neurons, each representing one of the possible diagnoses: Benign, Malignant, and Normal. The softmax activation function is used, which converts the outputs of the neurons into probabilities for each class.

Model Compilation: The model is compiled with sparse_categorical_crossentropy as the loss function, which is suitable for multi-class classification problems where the target labels are integer-encoded. The adam optimizer is used to update the model weights efficiently during training. The model is trained for 10 epochs with a size of 8 batch, meaning that it processes 8 images at a time, adjusting the weight after each batch.

TABLE I. CNN ARCHITECTURE

Layer Type	Output Shape	Number of Parameters
Input	(256, 256, 1)	0
Conv2D	(254, 254, 64)	640
MaxPooling2D	(127, 127, 64)	0
Conv2D	(125, 125, 64)	36,928
MaxPooling2D	(62, 62, 64)	0
Flatten	(246016)	0
Dense	(16)	3,936,272
Dense (Output)	(3)	51

According to Table I, the layers with 0 parameters (Input, MaxPooling2D, and Flatten) are often called "fixed function" layers. These layers perform a specific operation that didn't adjust during the training process. This is why those layers have 0 parameters. The total parameters (3,973,891) represent all the weights and biases that the network can adjust during training. The original 256x256 grayscale lung CT scan image enters the network and is immediately analyzed for basic features by the first convolutional layer, resulting in 64 feature

maps of size 254x254. These feature maps are then condensed by the first max pooling layer, keeping only the strongest signals and reducing the size to 127x127. The second convolutional layer further analyzes these condensed features for more complex patterns, producing 64 new feature maps of size 125x125. Another max pooling layer then condenses these complex feature maps to 62x62. The flattened layer stretches this 62x62x64 data cube into a single line of 246,016 numbers. These numbers are fed into a fully connected layer, which calculates 16 high-level features. Finally, the output layer uses these 16 high-level features to determine the final diagnosis probabilities for the three possible outcomes (Benign, Malignant, Normal). This entire process transforms the original image into a set of probabilities, indicating how likely the image belongs to each of the three categories, effectively turning a complex visual input into a simple, interpretable medical diagnosis.

E. Data Training

1. Data Augmentation and Balancing
   - Data Augmentation: Gaussian Blur were applied to increase the diversity of training data.
   - Balancing Class with SMOTE: SMOTE was used to generate synthetic samples for minority classes and ensure equal representation.
2. Model Compiling
   - Compiling Model: The custom CNN model was compiled using the Adam optimizer along with sparse categorical cross-entropy as the loss function.
   - Training Model: The training utilized a balanced dataset with a batch size of 8 over 10 epochs. This approach helped ensure that the model learned effectively from each class without bias towards any category.
3. Model Evaluation

Dataset Utilization

- The evaluation was conducted using a dataset obtained from Kaggle, specifically tailored for lung cancer detection.

Model Performance

- Custom CNN Model: The custom model demonstrated high accuracy in predictions. This model was specifically designed and trained on the dataset, allowing it to adapt better to the unique characteristics of the images.

IV. RESULTS

The performance of the custom CNN model is evaluated and compared with the pre-trained ResNet50 and VGG16 models. The custom CNN model achieved an accuracy of 98.55%, demonstrating its effectiveness in lung cancer detection. It provided competitive results with a precision of 98.90%, recall of 97.33%, and F1-score of 98.11%. The pre-trained ResNet50 model, leveraging its deep architecture and residual learning capabilities, attained an accuracy of 97.67%, with a precision of 98.00%, recall of 93.67%, and F1-score of 95.80%.

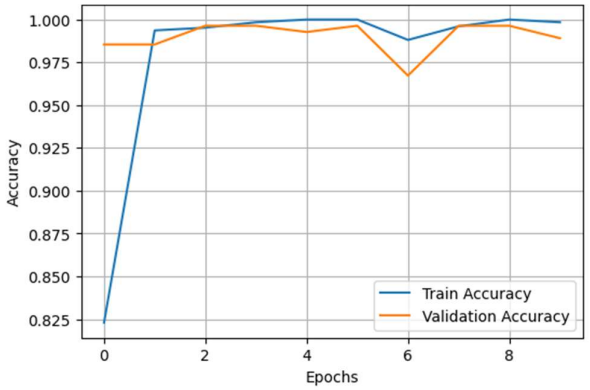

Fig. 2. Model Accuracy

The fine-tuned VGG16 model, known for its simplicity and effectiveness, reached an accuracy of 66.15%. These results highlight that the custom CNN, despite its simpler architecture, can perform with sophisticated pre-trained models. The enhancements such as data augmentation, handling class imbalance with SMOTE, and optimization strategies like early stopping and learning rate reduction contributed significantly to the custom model's high accuracy and robustness. This comparative analysis underscores the potential of the custom CNN model to deliver efficient and accurate solutions for medical image analysis, particularly in lung cancer detection. The accuracy graph (fig. 2) shows the accuracy over the training epochs for both training and validation sets. A consistently high validation accuracy indicates that the model performs well for unseen data.The loss graph (fig.3) shows the loss over the training epochs for both training and validation sets. A decreasing loss indicates the model is improving for the predictions.This study proves that carefully designed custom CNNs can be powerful tools for helping doctors find lung cancer in medical images, potentially leading to earlier detection and better patient care.

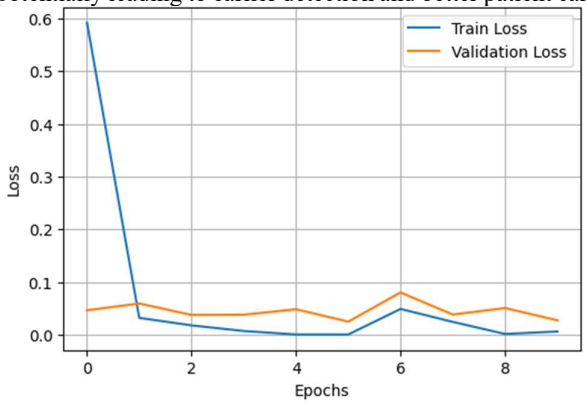

Fig. 3. Model Loss

V. CONCLUSION

This study demonstrates the effectiveness of a custom CNN model for lung cancer detection based on CT-Scan images of lungs, achieving superior performance (98.55% accuracy) compared to well-established pre-trained models like

ResNet50 (97.67%) and VGG16 (66.15%). The custom model, incorporating multiple Conv2D layers, MaxPooling2D layers, dropout, batch normalization, and advanced techniques such as SMOTE and data augmentation, proved highly effective in classifying lung cancer images. These results highlight that carefully tailored CNN architectures can match or exceed the performance of complex pre-trained models in specific medical imaging tasks, offering a more efficient and potentially more accurate solution for lung cancer detection. The study confirms that a custom CNN can outperform established models in lung cancer image classification, underscoring the importance of task-specific architecture design in medical image analysis. However, limitations include the use of a specific dataset, necessitating further validation of diverse datasets from multiple institutions, and the need for evaluation in clinical settings. Future research should explore advanced optimization techniques, extend this approach to other medical imaging tasks, investigate the integration of additional data sources like patient history or gene.

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