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Efficacy of Deep Learning Algorithms in Detecting Lung Cancer

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Abstract:- Lung cancer remains a major public health concern, demanding accurate and timely detection for improved patient outcomes. Deep learning algorithms have demonstrated remarkable potential in various medical applications in the past few years, including lung cancer detection. This study evaluates the effectiveness of deep learning algorithms for detecting lung cancer using diverse datasets of lung cancer images, including X- rays and CT scans. The results, characterized by high sensitivity and accuracy, were achieved using Convolutional Neural Networks (CNNs) that were employed. Overall, deep learning algorithms show great potential in revolutionizing lung cancer detection, leading to improved patient outcomes and early intervention. However, interpretability and trust in AI models remain concerns that medical settings need to address. Keras was chosen as the development tool due to its efficiency in quickly executing tasks. After conducting a comprehensive literature review, the study culminated in suggestions for advancing research and integrating findings into clinical applications.

I. INTRODUCTION

Among the various components of the human body, the lungs hold the utmost importance and significance. A common cause of lung dysfunction is the presence of lung tumors, which are essentially uncontrolled clusters of rapidly multiplying cells. The growth of these tumor cells leads to lung failure as they consume essential nutrients meant for cells and tissues. Clinicians currently manually examine the MR images of the lungs to determine the lung tumor's location and size of the patient, this process is time- consuming and often sometimes results in inaccurate detection.

Every year, a notable number of people die from lung cancer. Early diagnosis of the lung cancer is facilitated by techniques for identification and categorization. The classification of cancers in clinical diagnosis poses significant challenges. This research study is centered on utilizing a Convolutional Neural Network (CNN) model to analyze MRI scans from different patients in order to identify tumor masses and to classify the types of tumors.

Different techniques for image processing, like image segmentation, enhancement, and feature extraction, are used to identify lung tumors in MRI scans of cancer patients. Through the utilization of image processing techniques, the detection of lung cancers involves four key processes: Image preprocessing, segmentation, feature extraction, and classification are all part of the process. Combining image processing with neural network methods improves the accuracy of lung cancer detection and categorization in MRI images.

II. METHODOLOGY

A. Analysis of the Dataset

Data analysis is the process of investigating and interpreting data to find solutions. It's crucial for understanding survey and administrative results and effectively presenting data information. Through data analysis, insights are expected to be gained into various aspects of the study, such as exploring respondents' perceptions and enriching readers' understanding and interest in the research topic. Data analysis will be carried out using Jupyter notebook and scientific analysis tools (Burns, 2022).

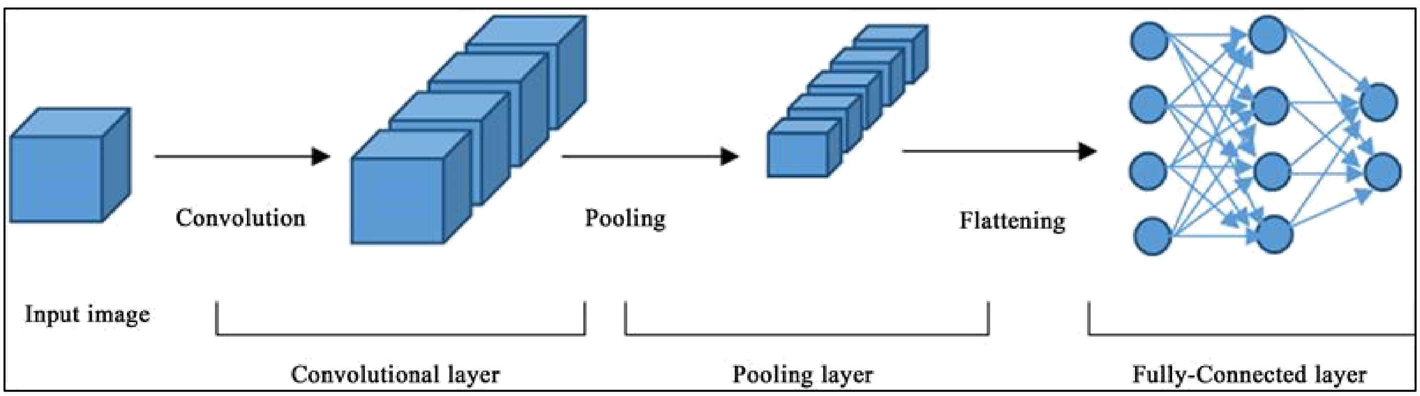

Fig 1: Basic 3D CNN Architecture

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B. Convolutional Neural Network CNN

CNN is widely used for image/object recognition and classification as a type of deep learning. A standard CNN comprises multiple layers, such as convolutional layers, pooling layers, and fully connected layers. The convolutional layers extract important characteristics from the input image, while the pooling layers decrease the size of these features to simplify the network's computations. Fully connected layers then utilize these extracted features to generate final predictions.

During the training process, convolutional layers learn filters or kernels, which are then applied to the input image to highlight specific features like edges and textures through mathematical operations.

The figure below presents the basic 3D CNN architecture.

C. Layers that makes up a CNN Model

In a simple CNN, each layer comprises a differentiable function that transforms one activation volume into another. The three main categories of layers used in constructing CNN architectures are:

➢ *A Convolutional Layer:*

A convolutional layer is a foundational component of a convolutional neural network (CNN), responsible for applying a convolution operation to the input data.

Within a convolutional layer, learnable filters (kernels) move across the input data, executing a mathematical operation called convolution. This process involves multiplying the filter values with corresponding input data values and then summing the outcomes. The result is a feature map that emphasizes specific patterns or features within the input data.

Convolutional layers are meant to extract meaningful features from images or other types of data with spatial relationships. By stacking multiple convolutional layers with nonlinear activation

Convolutional layers are computationally efficient and can effectively learn translation- invariant features, making them well-suited for image and signal processing tasks.

➢ *Some of the Basic Features of a Convolutional Neural Network Includes:*

- *Parameter Sharing:* This is the sharing of weights by all nodes in a particular neural network.
- *Local Connectivity:* Local connectivity refers to the idea that each node is only connected to a part of the input image. The efficiency of computation and the entire system's parameter count are influenced by these attributes. The output volume size of the convolution layer is governed by three hyper parameters.

➢ *The Hyper Parameters are:*

- *Stride:* When the stride is set to 1, the filters move one pixel at a time, navigating across the width and height of the input image to adjust the pointer. When stride is set to 2, the filters will move in increments of 2 pixels. When the stride is 1, a 2*2 filter passes through the width and height of the 4*4 input size.
- *Depth:* The depth of the input volume in the first layer corresponds to the number of color channels in the input image. For a colored image, with red, green, and blue channels, the depth is 3. In grayscale or black-and-white images, the depth is 1. The depth of the output volume is determined by the number of filters applied to the input.
- *Zero Padding:* This is the practice of occasionally expanding the input image with zero. Zero padding can be used to control the size of the input layer.

Without zero-padding, there's a risk of losing certain edge-related properties.

➢ *A Pooling Layer:*

A pooling layer is a standard component in convolutional neural networks (CNNs) used to reduce the spatial dimensionality of feature maps created by convolutional layers.

Pooling focuses on small local regions of feature maps, replacing values in each region with a single value summarizing those features. Two common pooling operations are max pooling and average pooling.

- Max pooling: Commonly used in CNNs, it selects the maximum value from its rectangular neighborhood.
- Average pooling: Returns the average value from its rectangular neighborhood.

➢ *A Fully-Connected Layer:*

A fully-connected layer, also called a dense layer, is a neural network layer where every node in one layer connects to every node in the next layer. Each node in the fully- connected layer receives input from every node in the preceding layer and produces an output transmitted to every node in the subsequent layer.

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- *Data Import and Preprocessing*

```
# Function to load and preprocess images
def load_and_preprocess_images(image_dir, resize_shape=(224, 224)):
    images = []
    for image_filename in os.listdir(image_dir):
        if image_filename.endswith('.jpg') or image_filename.endswith('.png'):
            image_path = os.path.join(image_dir, image_filename)
            image = Image.open(image_path)
            image = image.resize(resize_shape)
            image = np.array(image) / 255.0  # Normalize pixel values
            images.append(image)
    return np.array(images)
```

Fig 2: Preprocessing of the Imported Data

- *Class Distribution*

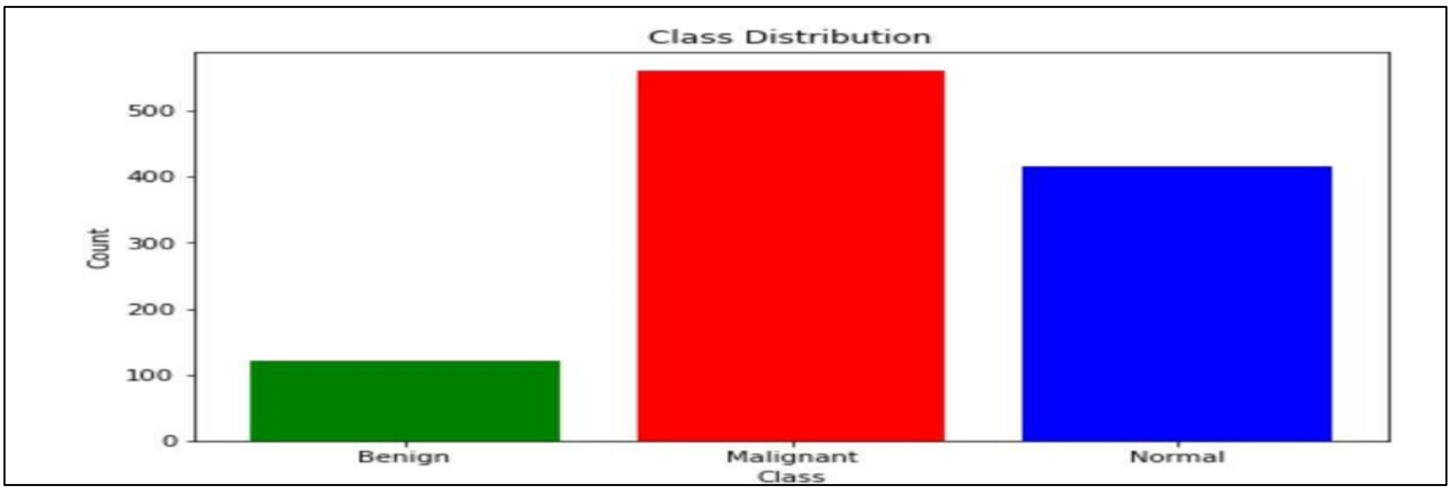

Fig 3: Class Distribution

- *Changing Pixel Values*

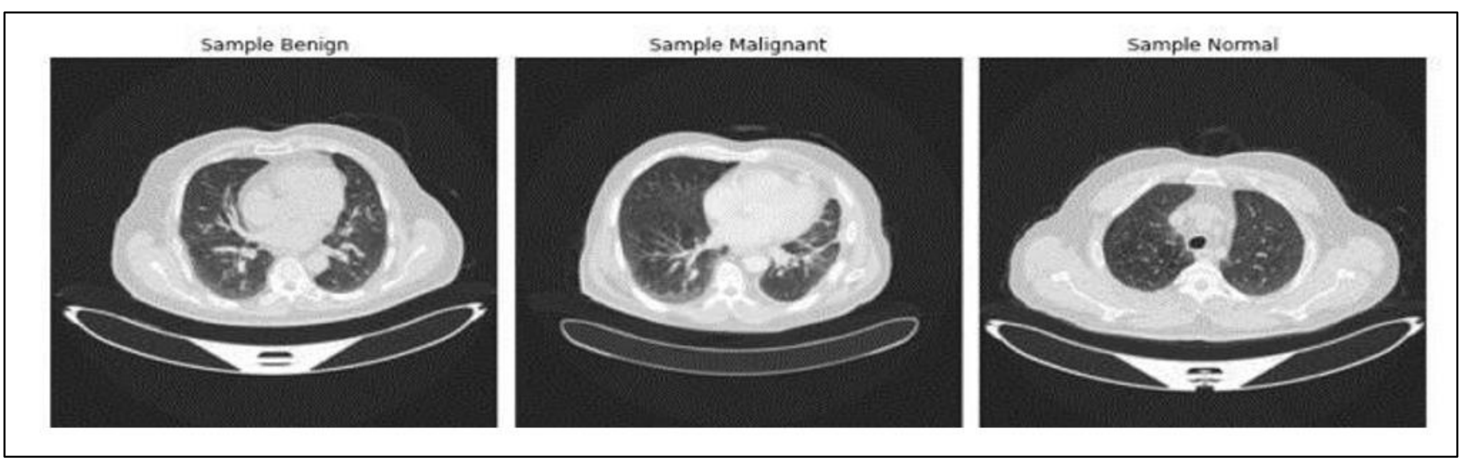

Fig 4: Changing Pixel Values

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D. Normalization

The images are collected sometimes with different sizes; normalization is very important to make all images have the same format.

The first step was to resize the images so that they can all have the same size, and normalizing the image pixels so that they can range between 0 and 1.

E. Deep Learning Model

Sequential model with CNN layers was used to train and predict the class of whether an inputted image has cancer in it or not.

F. Model Building

```
Layer (type)                    Output Shape              Param #
=================================================================
conv2d (Conv2D)                 (None, 510, 510, 32)      896

max_pooling2d (MaxPooling2      (None, 255, 255, 32)      0
D)

conv2d_1 (Conv2D)               (None, 253, 253, 64)      18496

max_pooling2d_1 (MaxPoolin      (None, 126, 126, 64)      0
g2D)

conv2d_2 (Conv2D)               (None, 124, 124, 64)      36928

max_pooling2d_2 (MaxPoolin      (None, 62, 62, 64)        0
g2D)

flatten (Flatten)               (None, 246016)            0

dense (Dense)                   (None, 128)               31490176

dense_1 (Dense)                 (None, 256)               33024

dense_2 (Dense)                 (None, 3)                 771

=================================================================
Total params: 31580291 (120.47 MB)
Trainable params: 31580291 (120.47 MB)
Non-trainable params: 0 (0.00 Byte)
```

G. Model Performance

The aim of this study was to leverage deep learning for constructing an effective model to detect lung cancer. In comparing training and test data, lower model loss should be observed in the training data. Our findings revealed the utility of employing deep learning algorithms such as Tensor Flow and Keras for classification tasks using neural networks. These frameworks provided the capability to address complex challenges, particularly when leveraging the robustness of convolutional networks. Maintaining lower model loss in training examples compared to test data is crucial. Understanding these foundational concepts and the learning curve can help avoid overfitting issues with these adaptable choices. The wider learning curve gap between training and test loss reflects the generalization disparity.

Accuracy is defined as the number of correctly predicted images.

```
Epoch 10/15
35/35 [==============================] - 346s 10s/step - loss: 0.0071 - accuracy: 0.9973 - val_loss: 0.0876 - val_accuracy: 0.9
839
Epoch 11/15
35/35 [==============================] - 342s 10s/step - loss: 0.0057 - accuracy: 0.9982 - val_loss: 0.1004 - val_accuracy: 0.9
839
Epoch 12/15
35/35 [==============================] - 338s 10s/step - loss: 0.0034 - accuracy: 0.9991 - val_loss: 0.1350 - val_accuracy: 0.9
731
```

Fig 6: Model Performance

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III. CONCLUSIONS OF THE STUDY

The identification of lung tumors holds significant importance in clinical treatment strategies. Understanding and interpreting medical imaging plays a crucial role due to the variability in image presentation. The utilization of an automated approach for lung tumor detection not only simplifies the detection process but also substantially enhances the chances of patient survival. Convolutional neural networks have become a leading technology for accurately and reliably identifying lung tumors. The classification of lung cancer represents the primary application of MRI technology.

Deep learning-based techniques have garnered increased attention and efficiency in the field of medical imaging owing to their demonstrated effectiveness in extracting features compared to traditional classification algorithms. Early detection of cancer and the accurate grading of tumors using rapid and cost-effective diagnostic tools have the potential to save numerous lives. Consequently, there is a pressing demand for swift, non-invasive, and cost-effective diagnostic methods in the medical field. This research aims to meet these critical needs by devising an innovative and advanced approach to improve the accuracy of lung tumor detection in MRI images.

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