CNN-Based Classification of Histopathology Images for the Diagnosis of Lung Cancer

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Abstract - Cancer is the uncontrollable division of abnormal cells that can spread to other organs. Lung cancer, the most common type in both men and women, includes two main types: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). NSCLC constitutes about 80 percent of lung cancer cases and typically spreads to other body parts, with subtypes including adenocarcinoma and squamous cell carcinoma. Diagnostic methods for lung cancer include X-rays, CT scans, bronchoscopy, and biopsy. Histopathology, the examination of biopsy samples by a pathologist, is crucial for diagnosing diseases by analysing tissue and cells. Histopathology image analysis offers more comprehensive diagnostic information compared to mammography and CT scans, especially for cancer grading. To expedite lung cancer diagnosis and alleviate the pathologist's workload, deep learning techniques are employed. Our proposed system utilizes Convolutional Neural Networks (CNN) combined with Rectified Linear Unit (ReLU) and Batch Normalization (BN) to enhance the diagnostic process.

Key Words: CNN, Rectified Linear Unit (ReLU), Batch Normalization (BN), Histopathology image.

1. INTRODUCTION

Lung cancer is one of the leading causes of cancer-related deaths worldwide. Early and accurate detection is crucial for improving patient outcomes. In this context, convolutional neural networks (CNNs), a class of deep learning models, have shown great promise in analyzing medical images for disease diagnosis.

2. Existing System

Lung cancer, recognized as one of the deadliest forms of cancer, underscores the crucial significance of early detection for successful treatment and improved survival rates. This existing system presents a comprehensive approach to lung cancer classification, employing advanced computational intelligence techniques. The system comprises three integral phases: lobe segmentation, candidate nodule extraction, and lung cancer classification. Utilizing a modified U-Net architecture, the system accurately segments CT scans to derive lobes, followed by candidate nodule extraction using predicted lobes as input. Further, a modified AlexNet-SVM model is applied to classify candidate nodules as either cancerous or non-cancerous, enhancing the precision of lung cancer diagnosis. Through this integrated approach, the system contributes to timely detection and classification, ultimately aiming to improve patient outcomes and survival rates in lung cancer management.

This holistic approach not only enhances diagnostic accuracy but also fosters a proactive paradigm in lung cancer care, ultimately translating into tangible improvements in patient outcomes and quality of life.

3. Proposed Algorithm

Convolutional Neural Network (CNN): CNN is a type of deep neural network particularly well-suited for image classification and recognition tasks. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNNs exploit spatial hierarchies of features in images through convolutions, enabling them to learn patterns and features directly from pixel values. Convolutional layers apply a set of learnable filters to input images, extracting various features such as edges, textures, and shapes. Pooling layers reduce the spatial dimensions of the feature maps produced by convolutional layers, helping to reduce computation and control overfitting. CNNs are trained end-to-end using gradient-based optimization algorithms like backpropagation, adjusting the network's parameters to minimize a loss function.

Rectified Linear Unit (ReLU): ReLU is an activation function commonly used in deep learning models, including CNNs. It introduces non-linearity into the network by replacing negative values with zero while leaving positive values unchanged. ReLU activation function $f(x)=\max(0,x)$ f(x)=max(0,x) is computationally efficient and helps alleviate the vanishing gradient problem during training. ReLU has become a standard choice for activation functions in CNNs due to its simplicity and effectiveness.

Batch Normalization: Batch Normalization is a technique used to improve the training of deep neural networks, particularly CNNs. It normalizes the activations of each layer within a mini-batch, reducing internal covariate shift and accelerating training. Batch Normalization operates by normalizing the output of each layer, typically by subtracting the mini-batch mean and dividing by the minibatch standard deviation. It introduces learnable parameters (scale and shift) for each channel, allowing the network to adaptively adjust the normalization. Batch Normalization can improve the training stability, allow for higher learning rates, and reduce the dependence on careful initialization of network weights. It has become a standard component in many deep learning architectures, contributing to their improved performance and convergence speed.

Data set Download the dataset from Kaggle using the Kaggle API. Preprocess the dataset by unzipping it and organizing it into training, validation, and test sets. Set parameters such as picture size, folder paths, and batch size

Methodology

1. Input Layer: Accepts images of size 224x224 pixels with 3 color channels (RGB), which is a common input size for many pre-trained CNN architectures.

2. Convolutional Layers: Consists of four Conv2D layers: The first layer has 32 filters, followed by ReLU activation and batch normalization. The subsequent layers follow a similar pattern but with increased filter sizes (64, 128, 256).Each convolutional layer extracts features from the input images using filters.

3. MaxPooling Layers: Includes four MaxPooling2D layers after each convolutional layer. Max pooling down samples the feature maps, reducing their spatial dimensions while retaining the most important information.

4. Flatten Layer: Flattens the output from the convolutional layers into a 1-dimensional tensor, preparing it for the fully connected layers.

5. Dense Layers: Contains two dense (fully connected) layers with 512 units each and ReLU activation. These layers perform high-level feature extraction and classification based on the features extracted by the convolutional layers. The final dense layer has 3 units (equal to the number of classes) with SoftMax activation, producing the probability distribution over the three classes of lung cancer.

6. Model Compilation: Compiled using the Adam optimizer, which is an adaptive learning rate optimization algorithm. Uses categorical cross-entropy as the loss function, suitable for multi-class classification tasks. The model is trained to minimize this loss function during training.

7. Training: Trained on the training set while validating its performance on the validation set. The training process adjusts the model's parameters (weights and biases) to minimize the loss function.

8. Evaluation: Evaluated on both the validation and test sets to assess its accuracy and generalization performance. Evaluate the trained model's performance on the validation set to assess its accuracy. Evaluate the model on the test set to obtain its performance metrics.

9. Metrics and Analysis: Additional metrics such as precision, recall, and F1-score are calculated to provide a more comprehensive evaluation of the model's performance. A confusion matrix is generated to visualize the model's classification results and identify any potential misclassifications. Calculate additional metrics such as precision, recall, and F1-score using sklearn.Generate a confusion matrix to visualize the model's performance in classifying different classes of lung cancer. Plot the confusion matrix to gain insights into the model's classification results.

10. Model Saving: The trained model is saved for future use, allowing for inference on new data without retraining.

5. System architecture

System Architecture of Lung Cancer Prediction Using CNN

The system architecture for lung cancer prediction using Convolutional Neural Networks (CNN) can be broken down into several key components. Here's an overview:

1. Data Acquisition:

Data Source: The dataset is obtained from Kaggle, containing preprocessed lung cancer images.

Data Preparation: The dataset is organized into training, validation, and test sets. Each set contains images categorized into different classes representing various stages or types of lung cancer.

2. Data Preprocessing:

Image Augmentation: Utilize ImageDataGenerator to preprocess the images. This can include operations like rescaling, normalization, and other transformations to augment the training data.

Data Loading: Load images from directories using flow from directory, specifying parameters such as target image size, color mode, batch size, and class mode.

3. Model Architecture:

Convolutional Layers: The model consists of multiple convolutional layers with ReLU activation functions, which help in feature extraction from the input images. Padding is used to preserve spatial dimensions.

Batch Normalization: After each convolutional layer, batch normalization is applied to stabilize and accelerate training.

Pooling Layers: MaxPooling layers are used to reduce spatial dimensions, thus decreasing computational load and controlling overfitting.

Flattening Layer: Converts the 2D feature maps into a 1D vector to feed into fully connected layers.

Fully Connected Layers: Dense layers are used to learn high-level representations and make predictions.

Output Layer: A SoftMax activation function in the final dense layer outputs probabilities for each class.

4. Model Compilation:

Optimizer: Adam optimizer is used for adjusting the learning rate during training.

Loss Function: Categorical cross entropy is used as the loss function, suitable for multi-class classification.

Metrics: Accuracy is monitored as the primary metric to evaluate model performance.

5. Model Training:

Training Process: The model is trained using the training set with a specified number of epochs, and its performance is validated on the validation set.

Early Stopping and Checkpoints: Implementing mechanisms like early stopping and model checkpoints can help in saving the best model and preventing overfitting.

6. Model Evaluation:

Validation and Test Evaluation: The model's performance is evaluated on the validation and test sets to ensure generalizability.

Metrics Calculation: Metrics such as loss and accuracy are computed for both validation and test sets.

7. Model Prediction and Analysis:

Predictions: Model predictions are made on the test set.

Confusion Matrix: A confusion matrix is plotted to visualize the performance across different classes, providing insights into misclassifications.

Classification Report: Precision, recall, and F1-score are computed to give a comprehensive evaluation of model performance.

8. Visualization:

Confusion Matrix Plot: The confusion matrix is visualized to understand the distribution of predictions versus actual labels.

Metrics Visualization: Precision, recall, and F1-score are displayed to provide a detailed performance analysis.

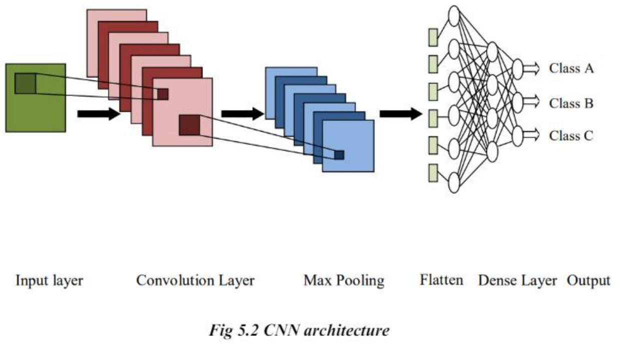

Fig -1: CNN architecture

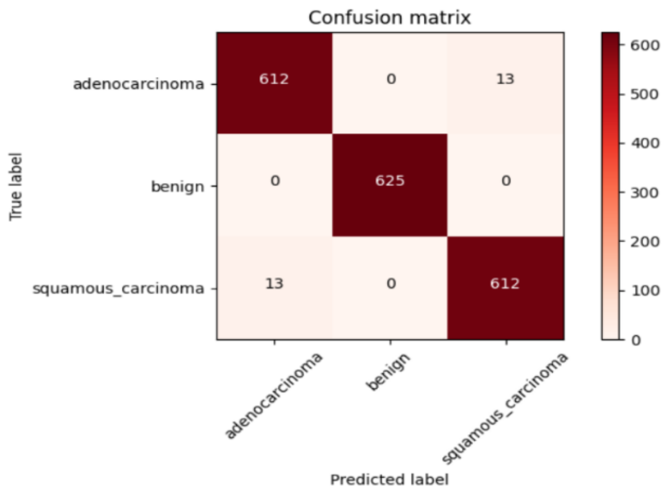

Fig -2: Confusion matrix

4. Future enhancement

In future, developing a real-time system for non-small cell lung cancer detection from histopathology images promises efficient classification and subtype analysis. This advancement would alleviate the burden on pathologists, offering rapid and accurate results while enabling them to focus on complex cases. With automated classification, timely treatment decisions can be made, potentially improving patient outcomes. The system's real-time capability ensures faster results, facilitating early detection and intervention for better prognosis.

5. CONCLUSION

In conclusion, our research endeavors aim to continually improve disease detection methodologies, leveraging advanced CNN-based models and real-time systems. By addressing challenges and enhancing efficiency, we strive to contribute to better patient outcomes and alleviate burdens on healthcare professionals. Through ongoing innovation and technological advancements, we aspire to make significant strides in disease detection and diagnosis. Our research focuses on advancing disease detection using CNN models and real-time systems, aiming to improve patient outcomes and alleviate burdens on healthcare professionals through innovation and efficiency enhancements.

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