Detection of Lung Cancer Through Histopathological Images.

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Abstract. Artificial intelligence (AI) is transforming medical diagnostics, particularly in the early detection of diseases such as lung cancer. This study evaluates the performance of two deep learning models—a custom convolutional neural network (CNN) and ResNet-50—in classifying lung cancer histopathological images. The ResNet-50 model demonstrated rapid convergence to its optimal training loss, while the custom CNN required more epochs to stabilize, indicating slower convergence. Despite this, the results were encouraging, as both models reached stability after a relatively small number of epochs. The findings highlight the potential of AI in enhancing diagnostic accuracy, and future work could explore dynamic parameterization, data augmentation, and transfer learning to further improve model robustness. Integrating AI-driven solutions into clinical workflows could revolutionize medical diagnostics, providing faster, more accurate, and reliable early detection of diseases.

Keywords. Convolutional Neural Networks, Medical Imaging Classification, Cancer Detection, Medical Image Processing.

1. Introduction

In recent years, lung cancer has emerged as one of the leading causes of mortality in Latin America [1]. The lack of adequate medical infrastructure, the shortage of healthcare professionals, and the limited acess to healthcare systems have contributed to the progression of the disease in many countries in the region [2]. In Brazil, this situation is even more concerning, as lung cancers ranks among the main causes of death in the country [3].

Given this scenario, the use of new technologies, such as deep learning, has intensified in an effort to develop more effective methods for cancer diagnosis, especially in its early stages [4]. These technologies enable the analysis of large volumes of medical data, such as computed tomography scans, X-ray, and biopsies, with the goal of identifying patterns and features that may indicate the presence of lung cancer.

1.1 Cancer

Cancer is caused by a cellular dysfunction that alters the normal development of cells, leading to their uncontrolled and accelerated proliferation, which contributes to the formation of a tumor [5].

Lung cancer, in particular, affects the alveolar gas exchange process, impairing the flow of oxygen and carbon dioxide. Due to its severity, it is responsible for a high number of deaths worldwide, especially when diagnosed at more advanced stages, which leads to a lower chance of cure and worse prognosis [6].

The most widely recognized histological classification of lung cancer in the global literature is that of the World Health Organization (WHO). The four main histological types, which account for 95% of cases, are: squamous cell carcinoma, adenocarcinoma, small cell undifferentiated carcinoma, and large cell undifferentiated carcinoma [7].

1.2 Histopathological Images

Histopathological images are microscopic images that represent biological samples of tissues from the human body or other organisms, with the goal of studying cellular and structural characteristics. These images can reveal both normal and abnormal biological structures, allowing pathologists to identify potential diseases such as cancer [8].

1.3 Artificial Intelligence

Artificial Intelligence (AI) is the field focused on creating systems capable of performing tasks that typically require human intelligence. According to John McCarthy, a pioneer in the area, AI is the science and engineering of developing intelligent mechanisms not limited to biological processes. Its goal is to build machines that can understand, learn, and solve problems, adapting to new situations as effectively as humans [9].

Artificial Intelligence has emerged as an innovative tool in the healthcare field, creating new opportunities to improve the quality of medical diagnostics [10].

1.4 Machine Learning

Machine Learning is a data analysis method that automates the creation of analytical models. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention [11].

Deep Learning is a type of machine learning that trains computers to perform tasks in a way that mimics human behavior, such as speech recognition, image identification, and predictions. Instead of organizing data to be processed through predefined equations, deep learning defines basic parameters about the data and trains the computer to learn autonomously by recognizing patterns across multiple processing layers [12].

1.5 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are architectures inspired by biological processes, designed to be trained to learn representations that are invariant to scale, translation, rotation, and other affine transformations [13]. One of the main challenges in pattern recognition in images is determining the best way to robustly represent the features of the data in a way that is resistant to factors such as lighting, orientation, pose, and occlusion, among others.

A convolutional neural network, as shown in Figure 1, is composed of several layers, each with a specific function to extract and process different types of information from the images.

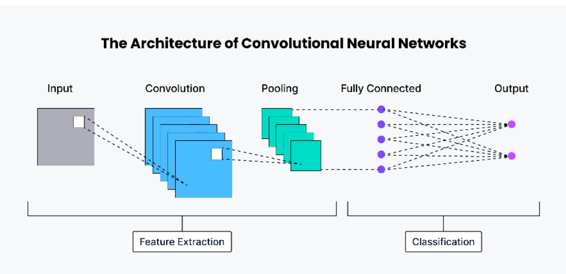

Fig. 1 – Convolutional Neural Network (CNN) architecture. From: Zilliz Glossary, Available from: https://zilliz.com/glossary/convolutional-neural-network.

The main layers of a CNN are:

- Convolutional Layer: The key feature of CNNs. It applies filters (or kernels) to an input image, performing convolution to detect features such as edges, textures, and simple patterns. As the image passes through the convolutional layers, the network learns to identify more complex features.
- Pooling Layer: After convolution, the pooling layer is used to reduce the dimensionality of the data while retaining the most relevant information. This layer helps to decrease computational complexity, improve efficiency, and reduce the risk of overfitting (when the model overfits to the training data, impairing its ability to generalize to new data).
- Fully Connected Layer (FC): In the final part of the network, fully connected layers are responsible for classifying the images. At this stage, the data processed by the previous layers are transformed into a one-dimensional vector, and each neuron in the output layer is connected to all the neurons in the previous layer.

To address the multi-class classification problem, a convolutional neural network can be designed using commonly adopted techniques in deep learning, including standard loss functions, optimization algorithms, and activation functions. These components are frequently chosen due to their demonstrated effectiveness in similar image classification tasks reported in the literature.

1.6 ResNet-50

Microsoft Research developed the CNN ResNet, which won the ILSVRC 2015 challenge. ResNet improved the traditional design of convolutional neural networks by incorporating 30 shortcut connections. These connections allow the output of one layer to be directly fed into a significantly deeper layer in the network. This feature increases resource efficiency and also helps mitigate the vanishing gradient problem. ResNet-50 is a variation of the original ResNet, using a depth of 50 layers, as illustrated in the diagram in Figure 2.

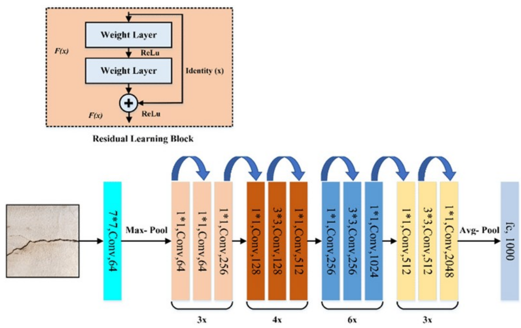

Fig. 2 – The architecture of ResNet-50 model. From: Performance Evaluation of Deep CNN-Based Crack Detection and Localization Techniques for Concrete

Structures – Figure on ResearchGate. Available from: https://www.researchgate.net/figure/The-architecture-of-ResNet-50-model_fig4_349717475.

2. Methodology

The objective of this study was to develop and evaluate a convolutional neural network (CNN) for the classification of lung cancer in histopathological images.

2.1 Materials

The computational resources required for this study consisted of a laptop with an active Google account. The code was developed and executed on Google Colab, taking advantage of the platform's free access to NVIDIA T4 GPUs. The integration between Google Colab and Kaggle was established through the use of an API key, enabling seamless data access and execution of the experiments in a cloud-based environment. The implementation was carried out using the Python programming language (v3.13.1), with the aid of the following libraries: scikit-learn (v1.6.1), NumPy (v2.2.2), PyTorch (v2.6.0), and Matplotlib (v3.10.1).

2.2 Data Acquisition and Preprocessing

This study employed the Lung Cancer Histopathological Images dataset, available on Kaggle, which comprises a total of 15,000 histopathological images equally distributed among three classes: adenocarcinoma, benign, and squamous cell carcinoma (5,000 images per class) [14]. For ease of processing, the images were organized into subdirectories according to their respective classes, allowing efficient loading during model training.

Figure 3 illustrates examples of histopathological images from the dataset used in this study, representing the three target classes.

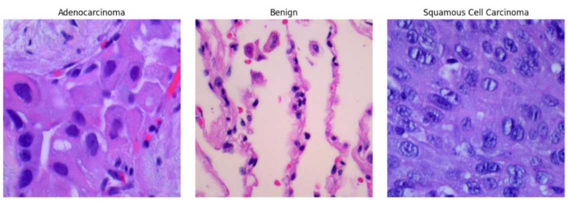

Fig. 3 – Representative Histopathological Images. Available from: Kaggle platform – https://www.kaggle.com/datasets/rm1000/lung-cancer-histopathological-images.

2.3 Image Transformations

All images were resized to 224 × 224 pixels to standardize input dimensions across the dataset. Following resizing, the images were converted into tensors and normalized using standard RGB mean and standard deviation values (mean = [0.485, 0.456, 0.406]; std = [0.229, 0.224, 0.225]). This normalization process is widely adopted in deep learning workflows and contributes to improved training stability and model performance.

2.4 Dataset Splitting

The dataset was split into 80% for training and 20% for validation.

2.5 Model Definition and Training

A simple convolutional neural network (CNN) architecture was implemented. It included two convolutional layers with 32 and 64 filters, respectively, each followed by a max pooling layer. Two fully connected layers were used to process features and generate outputs for the three classes. The Cross-Entropy Loss function was applied, as it is suitable for multi-class classification. Optimization was performed using Stochastic Gradient Descent (SGD) with a learning rate of 0.001 and momentum of 0.9. These values were selected based on a review of related literature. The model was trained for 50 epochs using mini-batches of 32 images. The Rectified Linear Unit (ReLU) activation function was used throughout the network to introduce non-linearity.

2.6 Model Evaluation

After training, the model was evaluated using the validation dataset. The accuracy was calculated by comparing the model’s predictions with the true classes of the images.

3. Results and Discussion

3.1 Custom Neural Network

Figure 4 shows the loss function progression over the training epochs of the convolutional neural network.

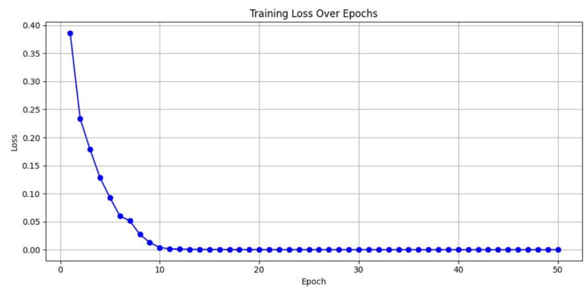

Fig. 4 – Loss Progression During Training – Custom Neural Network.

The analysis of the training loss over 50 epochs reveals the convergence behavior of the constructed neural network. The presented results indicate a significant improvement in model accuracy as the number of epochs increases. The loss consistently decreases, reflecting the network's continuous learning.

The model achieved a final accuracy of 94.90%, demonstrating promising performance in classifying histopathological images of lung cancer. Figure 5 provides a more detailed assessment of the predictions made for each class.

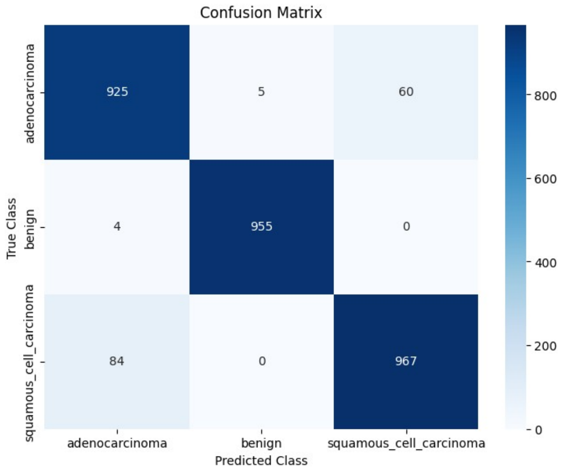

Fig. 5 – Confusion Matrix – Custom Neural Network.

The model demonstrated high accuracy in classifying the benign class, as evidenced by the minimal number of misclassifications. However, there was a recurring pattern of confusion between the adenocarcinoma and squamous cell carcinoma classes. A substantial number of adenocarcinoma samples were misclassified as squamous cell carcinoma, and vice versa. This suggests a degree of confusion between these two malignant classes, which may be attributed to morphological similarities in the histopathological features captured in the images. Further refinement of the model or the use of additional discriminative features may help improve differentiation between these cancer subtypes.

Prediction was made with the three images, and the network successfully predicted all of them correctly.

3.2 ResNet-50

Figure 6 shows the training loss of the ResNet-50 model across epochs.

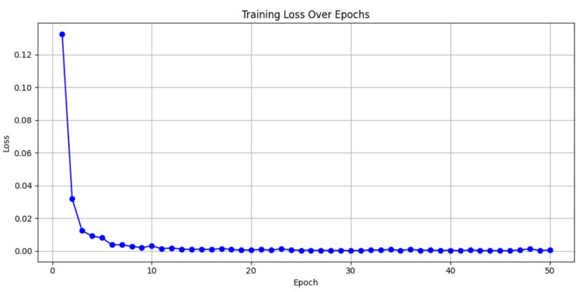

Fig. 6 – Loss Progression During Training – ResNet-50.

Initially, the loss decreases rapidly, indicating a swift reduction in error as the model learns from the training data. After a certain number of epochs, the loss stabilizes, suggesting that the model has reached convergence and further training does not result in significant improvements. This behavior is consistent with typical training dynamics, where the model quickly adapts in the early stages and then plateaus as it approaches optimal performance.

The model reached a final accuracy of 99.93%, indicating strong performance in the classification of histopathological lung cancer images. A more detailed evaluation of the class-wise predictions is presented in Figure 7.

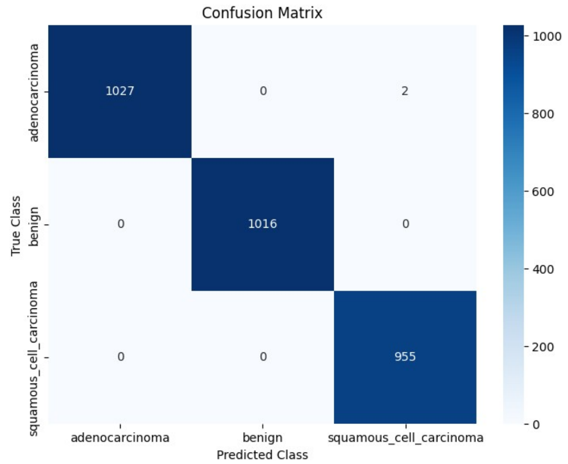

Fig. 7 – Confusion Matrix – ResNet-50.

The results demonstrate exceptionally high classification performance across all three classes. All benign and squamous cell carcinoma samples were classified with 100% accuracy, while only two adenocarcinoma samples were misclassified as squamous cell carcinoma. No confusion was observed between the benign class and the malignant classes, indicating that the model effectively distinguishes between benign and cancerous tissue. The extremely low number of misclassifications highlights the model's strong discriminative capability in identifying histopathological subtypes of lung cancer.

All three input images were accurately classified by the network, demonstrating its effectiveness in handling individual predictions.

3.3 Performance Comparison Between Custom CNN and ResNet-50

As shown in Figure 8, the training loss of the ResNet-50 model begins at a lower value and rapidly converges to its optimal point. In contrast, the custom CNN starts with a higher initial loss and requires more epochs to reach a stable state, indicating a slower convergence process.

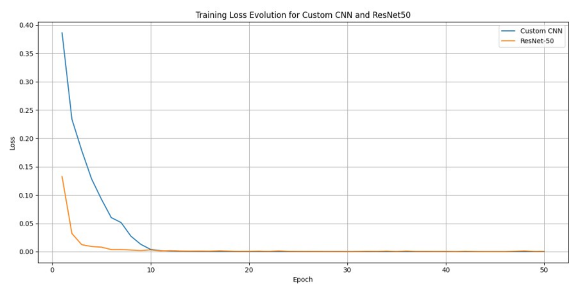

Fig. 8 – Training Loss Comparison Between Custom

CNN and ResNet-50.

However, both models reached stability in relatively few epochs, suggesting that the application of early stopping could be beneficial to prevent overfitting and reduce training time without compromising performance.

4. Conclusion

Artificial intelligence plays a pivotal role in the modernization of medical diagnoses, particularly in the early detection of diseases such as lung cancer. The efficiency of AI models, such as neural networks, allows for the rapid and accurate analysis of large datasets, such as histopathological images, enhancing the ability to detect patterns that may be overlooked by traditional methods. This significantly contributes to earlier and more accurate diagnoses, improving the chances of effective treatment.

This study compared the performance of a custom CNN and ResNet-50 in classifying lung cancer histopathological images. The ResNet-50 model demonstrated rapid convergence to its optimal training loss, starting from a lower value, while the custom CNN required more epochs to stabilize, indicating slower convergence. Both models stabilized in a relatively small number of epochs, indicating that early stopping could enhance training efficiency, minimize overfitting, and conserve computational resources, all while maintaining performance.

It is crucial to emphasize that model parameterization, such as adjusting loss functions and selecting the appropriate number of training epochs, plays a key role in ensuring model accuracy and reliability. One limitation of this study was the static parameterization, which may have restricted the models' potential for further optimization and adaptation during training. Future work could explore dynamic parameterization and additional optimization techniques to enhance model performance.

Furthermore, continuous improvements in model parameterization, including the exploration of data augmentation, transfer learning, and hyperparameter optimization, can significantly enhance model robustness and generalization. Techniques such as ensemble learning and the inclusion of multi-modal data could also improve accuracy, while ensuring models are trained on diverse datasets to mitigate biases.

Moreover, integrating real-time classification capabilities into clinical workflows, coupled with ongoing optimization of training protocols, will help bring AI-powered diagnostics closer to real-world applications. These continuous advancements in AI models will further increase the efficiency, accuracy, and applicability of AI in medical diagnostics, particularly in early disease detection.

5. References

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