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Classification of Multi Cancer using Deep Learning

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Abstract

A significant challenge in computational pathology is accurate and efficient classification of multiple cancers which have enormous potential for early detection and improved patient outcomes. To identify eight types of cancers using a sizable collection of 1,30,000 histopathological images to identify various types of cancer, 3 deep learning models are compared. DenseNet201, MobileNetV2, and VGG16 were all trained and tested individually. Important performance metrics such as accuracy, loss and per-class precision were used to evaluate models, comprehensive findings are displayed in confusion matrices. According to our analysis, MobileNetV2 is the most effective model, with the lowest loss of 0.0016 and the highest accuracy of 0.9998. Next was VGG16, which had a loss of 0.0058 and an accuracy of 0.9990. Despite having a high accuracy of 0.9980, DenseNet201's loss graphs indicated some instability during validation. MobileNetV2's reliable nature was demonstrated by the confusion matrix, which revealed it had few errors. These findings demonstrate that MobileNetV2 is most reliable and efficient option for this kind of cancer classification, making it a solid contender for application in automated diagnostic systems.

Introduction

Lakhs of new cases of cancer are reported yearly, making it one of World's most serious health issues [1]. Accurate and timely diagnosis is crucial to improving patients' health. Histopathological analysis involves looking at tissue samples under a microscope, has historically been used to make diagnoses [1]. Although successful, this procedure can be time consuming, subjective and differ from physician to physician [2]. There is a great need for more rapid, consistent, and reliable methods of diagnosis because more cases are appearing on a regular basis.

Artificial intelligence, particularly deep learning, has demonstrated significant promise in analysis of medical images in recent years it's a landmark clinical validation study that perfectly supports this claim. Change to [2][3][4]. Convolutional Neural Networks (CNNs), one of the various deep learning techniques, have emerged as powerful tool for this task. Known for their capacity to recognize intricate patterns in images, CNNs are especially useful for detecting cancer in tissue samples [2]. This study uses 1,30,000 histopathological images to classify eight different types of cancer. To find the optimal combination of accuracy, speed, and reliability, three CNN models: VGG16, DenseNet201, and MobileNetV2 are trained and compared. Finding best model for practical medical applications is the aim to speed up and improve accuracy of cancer diagnosis.

Literature Review

Histopathological examination involves examining tissue samples under a microscope, is primary method of diagnosing cancer [1]. This method is regarded as high standard for detecting cancer. There are certain issues with this procedure. It is labor-intensive, which requires highly qualified pathologists. Different physicians may have different perspectives that could result in inconsistent outcomes. The demand for pathology services is growing along with the number of cancer cases worldwide. It is crucial to have instruments that can speed up and improve the accuracy of the diagnostic procedure.

Computational pathology has made significant progress in addressing these issues, primarily due to advancements in deep learning. CNN primarily succeeded to be very efficient in analysis of medical histopathological images. In contrast to previous methods that depend on human sources to find features, CNN can automatically recognize leads from the source images [2]. This allows them to recognize minor details that may identify cancer, frequently matching proficiency of human experts in works like detecting cancer. CNN models come in different forms, each with advantages that others do not have. Notable architectures such as ResNet [5] introduced skip connections that solve vanishing gradient problems in very deep networks [6]. Medical image studies frequently begin with the VGG16 model, renowned for its straightforward and reliable structure [7]. DenseNet201 employs a unique method of layer connections that facilitates feature reuse and enhances the model's learning capacity, resulting in improved performance on challenging tasks [8]. Because MobileNetV2 uses a particular kind of convolution to maintain high performance while keeping the model small, it is well-suited for rapid analysis [9]. Fewer studies compare these models across a broad range of cancer types, even though they have been used to classify various cancers [10]. By directly comparing these three models on a sizable, diverse set of cancer data, this study tries to close that gap and determine which model is most effective for a general tool.

Lakhs of new cases of cancer are discovered in various nations each year which makes cancer a major global health concern. Early and accurate detection of cancer is critical to increasing patients' chances of recovery and survival. Histopathological analysis is typically used to diagnose cancer which involves looking at tissue samples under a microscope. Although this approach is thought to be best, it can be time consuming and labor intensive, and different experts may have different perspectives, which could result in errors or misunderstandings. This process becomes more difficult as we move forward with the increasing number of cases, there is a great requirement for more fast, efficient, more trustworthy, and more effective ways to help with the diagnosis. AI, more precisely deep learning, has shown significant trust in evaluation of medical images in past. CNN is a deep learning model that helps at identifying visual leads, which makes them accurate for tasks like recognizing cancer with the help of images. These models find new ways for helping experts in evaluating by finding features in source images that can be too minor or difficult for a human like us to identify. This work evaluates the complexity of assigning deep learning models to recognize different cancer subtypes. This work's primary goal is to make a way of differentiating between 8 distinct cancers by finding a collection of 1,30,000 histopathological medical images. We compared 3 most popular CNN models: VGG16, DenseNet201, and MobileNetV2, to find which model excels among all the best. To find which model gives the most accurate balance of accuracy, speed, and consistency, each model is trained individually. The study's findings are intended to demonstrate which model is best suited for application in actual medical settings to speed up and improve the accuracy of cancer diagnosis.

Methodology

Overview

We narrowed down the critical components of our work: the dataset we found, preprocessing steps and architecture of models we chose. The main goal was to find how good three different pre-trained deep learning models (VGG16, DenseNet201 and MobileNetV2) can handle difficult tasks of differentiating medical images. Focus was on identifying their accuracy and overall efficacy across cancer subtypes.

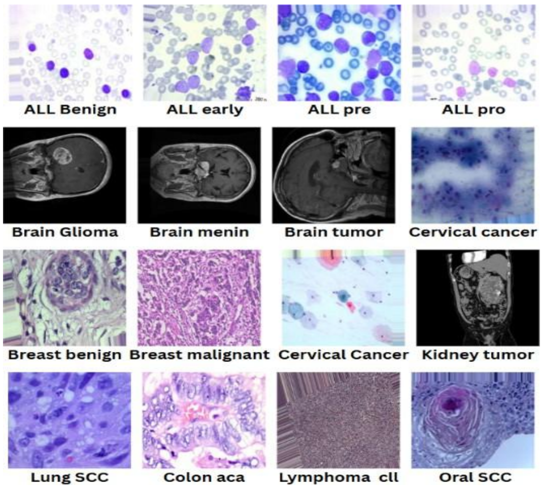

Figure 1: Multicancer Dataset images

Dataset Description

We found our training data from Kaggle's 'Multi Cancer' Dataset [11]. It is a large dataset which contains 1,30,000 medical images that have different categories of cancer and its subtypes. These images are further divided into subcategories. The distribution of the images is presented in Table 1 and sample histopathological images from each cancer category is shown in Figure 1.

Table 1: Distribution of Images Across Different Cancer Types

Cancer Type	**Number of Images**
Acute Lymphoblastic Leukemia	20,000
Brain Cancer	15,000
Breast Cancer	10,000
Cervical Cancer	25,000
Kidney Cancer	10,000
Lung and Colon Cancer	25,000
Lymphoma	15,000
Oral Cancer	10,000
Total	**1,30,000**

Each image is associated with specific types of cancer or subtypes making datasets appropriate for multi-class classification tasks. The dataset is diverse and well-balanced which helps effectively training Convolutional Neural Networks (CNN) models.

Data pre-processing

All images were made in the same size (224 x 224 pixels) to ensure they all fit the same input size for models used. After that dataset was divided into two distinct groups:

- **Training Set:** 80% of all images
- **Validation Set:** 20% of all images

Validation set was used to assess performance and track training progress. Data loading was handled using TensorFlow's image_dataset_from_directory function with the validation_split parameter set to 0.2 for consistent splitting.

Before the training began, all pixel values were changed to fall between 0 and 1 before. To improve model's performance and to prevent it from learning too much from training data, various techniques were also employed. These techniques included: flipping images from top to bottom or left to right, rotating them randomly, zooming in or out, and moving them slightly in different directions.

Model Architectures

Three deep learning models were implemented for comparison:

- **VGG16:** 16-layer CNN that uses sequential convolutional and pooling layers [7].
- **DenseNet201:** Densely connected CNN that allows for efficient feature reuse and helps reduce vanishing gradients [8].
- **MobileNetV2:** This architecture prioritizes speed and efficiency, using a combination of inverted residuals and linear bottlenecks to keep the model lightweight [9].

All models started with weights that were already trained on ImageNet dataset [12].. Then, transfer learning and fine-tuning methods were used to adjust the models for the multicancer dataset.

Experimental Setup

The models were built using TensorFlow and Keras. Training was performed for 10 epochs with a batch size of 16. The Adam optimizer with its standard settings was used, and categorical cross-entropy was chosen as the loss function to help improve predictions for multiple classes. The training was carried out.

Evaluation Metrics

The models were evaluated using the validation dataset. The metrics used include:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

These metrics helped in assessing each model's performance. Among the 3 models, MobileNetV2 performed the best, offering a good balance between accuracy and computational efficiency.

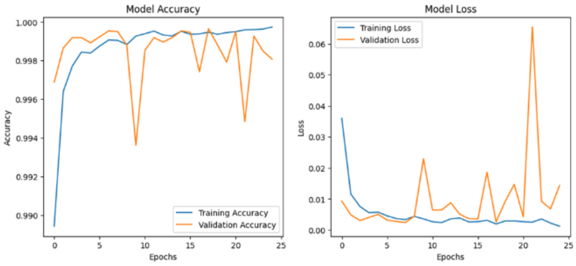

Figure 2: Training vs. Validation Accuracy Graph (DenseNet)

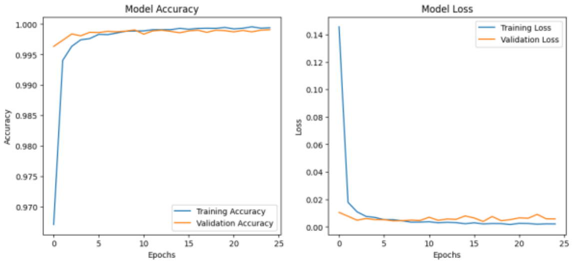

Figure 3: Training vs. Validation Accuracy Graph (VGG16)

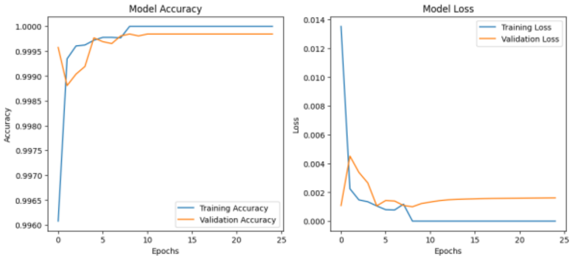

Figure 4: Training vs. Validation Accuracy Graph (MobilenetV2)

Results And Discussion

Model Performance

In this study, we utilized the Multicancer dataset to benchmark three specific pre-trained architectures: VGG16, DenseNet201 and MobileNetV2. Our goal was to find which deep learning model gave the most accurate result across the different cancer categories.

To compute stability and precision of each CNN, we experimented with validation accuracy and losses on a training of 25 to 30 epochs. The training and validation accuracy curves for DenseNet201 are illustrated in Figure 2, where mild instability during validation can be observed whereas as seen in Figure 3, VGG16 shows a steady convergence pattern across epochs, reflecting consistent learning behavior.

Table 2: Performance Comparison of Deep Learning Models on Multicancer Dataset

Model	**Accuracy**	**Loss**	**Epochs**
VGG16	0.9990	0.0058	25–30
DenseNet201	0.9980	0.01438	25–30
MobileNetV2	0.9998	0.0016	25–30

We found MobileNetV2 as the top performer, which achieved validation accuracy of 99.98% with a small loss as shown in Table 2. Figure 4 confirms MobileNetV2's smooth and stable convergence, with training and validation accuracy curves closely aligned throughout all epochs.

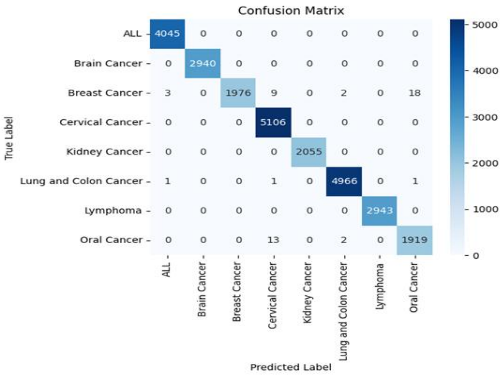

Figure 5: Confusion Matrix for DenseNet Model

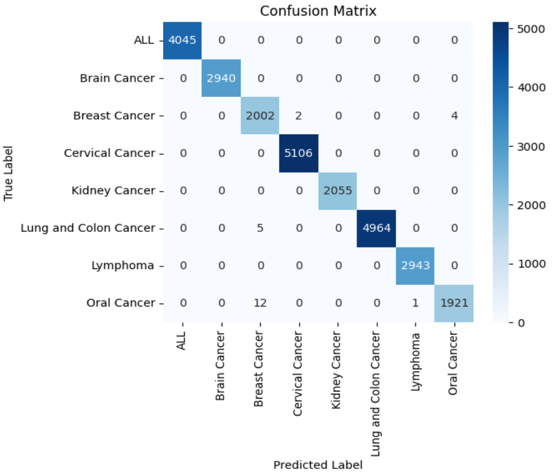

Figure 6: Confusion Matrix for VGG16 Model

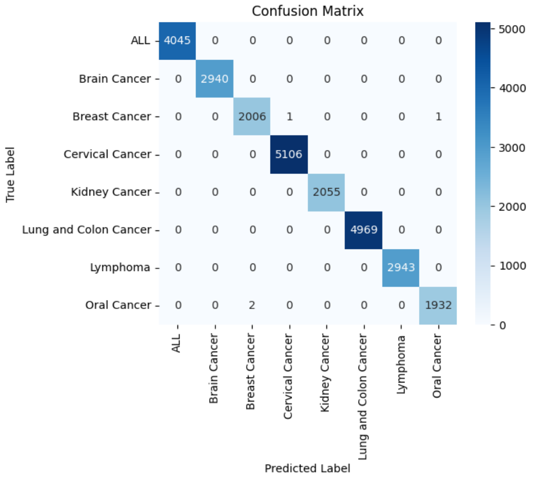

Figure 7: Confusion Matrix for MobilenetV2

of 0.0016. Getting the highest accuracy, it indicates that MobileNetV2 also shows significant convergence behavior and better generalization capability when we compare this with the other evaluated architectures.

Confusion Matrix Analysis

To find accurately at which part models were success or failure, we made confusion matrix for each. This allows us to find how differently each model can differentiate cancer types.

Both DenseNet201 and VGG16 showed steep diagonal lines as present in Figure 5 and Figure 6 respectively, a clear indication of high accuracy. Moreover, they did fail in some areas. This Data shows different classifications where CNN models confused between oral cancer with cervical cancer due to same looking in tissue structure.

Comparative Discussion

While VGG16 proves high accuracy (99.90%), the way it is structurally complex created a bottleneck, which shows result in slower training and increased memory load. DenseNet201 tops in efficiency because of its reuse capabilities feature. This didn't get the exact report correctly to the error rates, as it recorded a validation loss which was marginally higher than both the VGG16 and MobileNetV2.

Meanwhile, MobileNetV2 offered best ratio of efficiency to accuracy. It is ideal for use in real-world medical diagnostic systems, particularly those on mobile or edge devices as visualized in Figure 7, because of its lightweight design, which made it quicker to train and operate.

Summary of Findings

The experimental findings verify that nearly flawless cancer image classification from histopathological samples can be achieved by using pre-trained CNN models for transfer learning.

MobileNetV2 outperformed all the other models that were tested, demonstrating high accuracy, minimal loss and effective use of computational resources.

Conclusion And Future Scope

Conclusion

This study used publicly available *Multi Cancer* dataset to compare 3 deep learning models for classifying cancer images into multiple categories: VGG16, DenseNet201 and MobileNetV2. More than 1,30,000 histopathological images from eight major cancer types are included in dataset. To make sure models worked well in a variety of scenarios, these photos were processed and improved.

Transfer learning was used to train all 3 models and common performance metrics were used to assess each model. The data paints a clear picture: every model we tested successfully broke 99% accuracy threshold. MobileNetV2 was as the validation loss was only 0.0016 and accuracy was at 99.98%, it provides speed and accuracy that other models might not provide.

This work highlights key points: we can easily use CNNs for imaging tasks without getting a high computational cost. By using these systems into medical workflows, we can help experts in identifying cancer faster with high accuracy leading to accurate results for patients.

Future Scope

To develop this work further in coming future we intend to focus on the following points:

- **Dataset Enhancement:** For a better result we need to have a large dataset that models use for training. We can add more subtypes of cancer in the dataset to diversify it.
- **Hybrid Architectures:** CNNs and transformer-based models can be combined, and ensemble or majority voting strategies can further improve classification accuracy and feature representation.
- **Real-Time Deployment:** MobileNetV2 can be deployed in mobile or web-based diagnostic systems for real-time cancer detection in hospitals or remote healthcare settings due to its lightweight architecture and high accuracy.
- **Integration with Clinical Workflows:** In future, deep learning models might be incorporated into hospital in- formation systems to automate diagnostic reporting and doctors can make decisions with help of it.
- **Model Interpretability**: Explainability tools [13] can be incorporated to help clinicians understand and trust model predictions, which is critical for adoption in real clinical environments Explainability tools such as LIME [14] and Grad-CAM [14]can generate visual explanations highlighting which tissue regions influenced a prediction

Summary

In conclusion, the study demonstrates that MobileNetV2 model is highly appropriate for use in medical diagnosis and the transfer learning performs well for classifying cancer images into several categories. The results suggest a clear pathway for using Ai Frameworks into medical workflows which helps in the problems earlier and plan their treatments accordingly which helps in ultimately improving patient care.

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