Paper 1: P. Ghadekar, A. Khandelwal, P. Roy, A. Gawas and C. Joshi, "Histopathological Cancer Detection using Deep Learning," 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV), Gandhinagar, India, 2021, pp. 1-6, doi: 10.1109/AIMV53313.2021.9670991

Dataset: Histopathologic Cancer Detection | Kaggle

Paper Goal:

The goal of the paper is to propose a system for cancer detection using histopathological scanned images. The system utilizes transfer learning in Convolutional Neural Networks (CNNs), specifically employing the ResNet 50 model. The objective is to classify whether a given lymph node scan is cancerous or non-cancerous.

The Dataset Used:

The dataset utilized in this study is the PatchCamelyon benchmark dataset, obtained from the Kaggle platform. This dataset consists of small patches of images derived from a large-scale pathology examination. It includes 220,025 training images and 57,458 test images, making a total of 277,483 images.

The Models Used:

The primary model employed in this study is ResNet 50, a deep convolutional neural network with 50 layers. It utilizes residual connections to facilitate training of very deep networks. This architecture is known for its effectiveness in image classification tasks.

All Results and What Compared With:

The proposed system achieved an accuracy of 95% in classifying whether a lymph node scan is cancerous or non-cancerous. Unfortunately, specific details about other results or comparisons are not provided in the provided text.

Metric Used:

The main metric used to evaluate the performance of the proposed system is accuracy. Accuracy measures the proportion of correctly classified instances out of the total instances in the dataset. In this context, it signifies the percentage of correct classifications of cancerous and non-cancerous lymph node scans.

Paper 2 : M. Wang and X. Gong, "Metastatic Cancer Image Binary Classification Based on Resnet Model," 2020 IEEE 20th International Conference on Communication Technology (ICCT), Nanning, China, 2020, pp. 1356-1359, doi: 10.1109/ICCT50939.2020.9295797.

Dataset: basveeling/pcam: The PatchCamelyon (PCam) deep learning classification benchmark. (github.com)

Paper Goal

The goal of the paper is to address the task of metastatic cancer detection through image classification. The authors propose a new method based on the ResNet model, aiming to achieve superior performance in classifying small patch-level images of metastatic cancer. The proposed method is evaluated on the PatchCamelyon (PCam) benchmark dataset

The Dataset Used

The dataset used in this paper is the PatchCamelyon (PCam) benchmark dataset. This dataset is specifically modified for the study and contains 220,025 image samples. Among these, there are 89,117 positive samples (representing cancer) and 130,908 negative samples (representing non-cancer or normal images)

The Models Used

The primary model used in this paper is the ResNet (Residual Neural Network) model, as proposed by He et al. [3]. The ResNet model is chosen for its ability to train deep networks effectively and mitigate problems related to gradient disappearance and explosion

All Results and What Compared With

Models	**AUC , ROC score**	**Accuracy**
Vgg16	0.951	0.957
Vgg19	0.955	0.962
ResNet50	0.963	0.972

This table showing the performance of the ResNet50 model compared with other models, including VGG19 and VGG16. The results indicate that the ResNet50 model outperforms the other models in terms of Accuracy and AUC-ROC score. Specifically, the ResNet50 model achieves 1.0% higher accuracy than VGG19, and 1.2% higher AUC-ROC score and 1.5% higher accuracy than VGG16

Metric Used

The evaluation metrics used in this paper are AUC-ROC score and Accuracy. AUC-ROC (Area Under the Receiver Operating Characteristic curve) score is used to assess the performance of the classifier. It measures the area under the ROC curve, which reflects the classifier's ability to distinguish between the two classes (cancer and non-cancer). Accuracy is calculated as the sum of true positives and true negatives divided by the total number of samples. It provides an overall measure of the model's correctness in classifying images