

Deep Learning for Lung and Colon Cancer Detection with Explainable Artificial-Intelligence(AI)

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Abstract: Cancer diagnosis using histopathological imaging is an important task for medical imaging that requires a deep, accurate and interpretable learning model. This study proposes a deep learning framework that employs the Inception ResnetV2 model with LBP feature extraction (local binary pattern) to improve detection of lung and colon cancer. Our approach combines folding networks (CNNS) with handmade texture features to improve the classification performance of published histopathological data records. To ensure transparency and confidence in AI control decisions, we integrate explanatory KI (XAI) technologies, including Shapley Additive Description (SHAP) and LOCAL Interpretable Model Aggregation Declaration (LIME), to provide model interpretability. The proposed method achieves high accuracy, accuracy, recall, AUC-ROC results, surpassing traditional models. Characteristic visualizations illustrate key areas that influence predictions and provide insight into deep learning decision making. This study closes the gap between the accuracy and explanation of medical AI and provides a robust and interpretable solution for cancer detection.

Index Terms: Deep Learning, Lung Cancer, Colon Cancer, Histopathology, Explainable AI, Inception-ResNetV2, SHAP, LIME.

1. Introduction

Cancer is still one of the main causes of death in the world. Lung and colon cancer are among the most common types. Cancer cells have a high likelihood of growth in an autologous manner, genome instability, and metastasizing. All of this is very crucial in improving patient survival. Lung cancer is associated with the lungs in relation to uncontrolled cells - pro-musing and it makes up 18.4 percent of the world cancer-associated deaths. Colon cancer, a.k.a. colon cancer occurs in the large intestines or rectum and makes up 9.2 percent of the world cancer deaths (Bray et al., 2018; Bermoldezetal, 2021). The incidence of lung and colon cancer is equal to about 17 percent and without detection or screening of early cases, the risk of metastasis between the two noted organs is even greater (ACAR, until 2021). Under these, histopathological imaging analysis needs to discover new gold standards for cancer diagnosis, as it provides a direct visual confirmation of malignant cells. However, manual assessment of biopsy object carriers by pathologists is a time- and subjective process that deals with expert evaluations (Yeh et al., 2016). With advances in Artificial-Intelligence (AI) and deep learning, automated diagnostic systems have become contributing to cancer detection in histopathological images, which improves the efficiency and accuracy of Ditagal images (Sakib et al., 2022). Cancer recognition. However, existing studies often focus on either lung or colon cancer, with limited trials for co-classification. Previous studies have examined deep learning architectures such as Reset,

darknet19, and SVM classifiers. These achieved high classification accuracy of 93 percent to 99.69 percent (Bukhari et al., 2020; Hatuwal Thapa, 2020; Nishio et al. These models have high prediction accuracy, but suffer from the lack of interpretability of significant limitations. The deep learning model acts as a black box, making it difficult to explain decisions in medical applications.

2. Literature Survey

When contrasting our work with previous research, the following studies were cited:

2.1. *New Hybrid Neural Network to Detect Early Lung Cancer*

In this , we proposed a hybrid deep learning media (CCDCHIN) network (3D-CNN) using a recurrent neural network walk (RNN) for early detection of LUNG Records. While 3D-CNN recorded spatial features, RNN model time dependence and improved classification performance between benign and malignant tumors. Although this approach showed an important promise, the paper did not report explicit accuracy values. This indicates further performance validation.

2.2. *Detection of lung and colon cancer for machine learning using feature depth and extraction for ensemble learning*

This study implemented a hybrid ensemble framework trained on the LC25000 dataset. There, the extraction of deep functions from listed CNNs such as VGG16 and seals was integrated. The system achieved high classification accuracy of 99.05 percent for lung cancer, 100 percent for large- scale cancer, and 99.30 percent for combined detection.

2.3. *Transfer-based cancer detection using Inception-Resnetv2 using Explanatory AI*

We recorded texture information supplemented with local binary patterns (LBP) functionality using Inception-Resnetv2 architecture of the LC25000 dataset. By enabling SHAP, transparent decision- making is now possible. This model achieved excellent accuracy of 99.98 percent, combining high accuracy with clinical acceptance and trust interpretability. Although these methods have excellent accuracy, new interpretability, and continued efforts to improve generalization, the validation cross- data set validation and clinical provisions for real-world use are yet to be validated and clinically defined.

3. Design

3.1. *Overview of the System*

The system follows a structured river in which histopathological images are processed, properties are extracted, deep learning models are trained, and results are analyzed and interpreted. The key components of the system are:

- Data Acquisition.
- Preprocessing.
- Feature Extraction (LBP).
- Model Architecture (Inception-ResNetV2).
- Training and Evaluation.
- Explainability (SHAP and LIME).
- Final Prediction Output

3.2. *Data Acquisition*

This system uses LC25000 data records. This is a collection of histopathological images containing mark data for pulmonary and colon tissues in 5 classes:

- Colon-adenocarcinoma.
- Benign-colonic-tissue.
- Lung-adenocarcinoma.
- Benign-lung-tissue.
- Lung-squamous-cell-carcinoma

These images serve as inputs for model training, and the associated labels help to supervised learning.

3.3. *Data Preprocessing*

Data preprocessing is the function of preparing images to model effectively. The steps are:

- Resizing: All images are modified with uniform dimensions of 768 x 768 pixels to ensure consistency and optimize the input variables in the model.
- Normalization: The pixel values are normalized by dividing the area between 0 and 1 by 255. This step improves the convergence of the model during training.
- Data Augmentation: Images are used to increase the size of data sets using techniques such as drotation, oddity, and random cultivation.
- Splitting: Data records are divided into training (80 percent) and testing (20 percent) to assess the power of the model into invisible data.

3.4. *Feature Extraction (Local-Binary-Pattern - LBP)*

Local features of binary patterns (LBP) are extracted from the photos to improve the model's ability to record detailed texture information. LBP is a simple but powerful texture descriptor that captures local patterns in a photo based on the intensity of adjacent pixels. The step-by-step process is as follows:

- Neighborhood Comparison: Compare the surrounding pixels and values of each pixel (usually a 3x3 or 5x5 window).
- Binary Encoding: Each comparison leads to a binary value (1 or 0) indicating whether adjacent pixels are greater than the central pixel.
- Histogram Construction: A histogram of these binary values is created to represent texture for each image area. These histograms are used as additional features in the deep learning model. By including the LBP function, texture variation systems can be better captured at the micro-level, which is essential for distinguishing benign and malignant tissue.

3.5. *Model Architecture (Inception-ResNetV2)*

The model architecture chosen for this system is Inception-Resnetv2. This is a hybrid deep learning model that combines the efficiency of Inception modules with the robustness of residual connections from reset. This is how the architecture works:

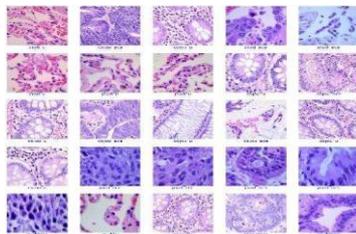
- Inception Modules: These modules rotate different sizes (1x1, 3x3, 5x5, etc.) in parallel so that the model can learn multi-scale characteristics.
- Residual Connections: The ResNet component uses skip connections to allow the model to learn a deeper representation without any flight gradient issues.
- Transfer Learning: This model is trained on a large image dataset, such as Imageet, and can learn common functions such as edges and textures. These pre-hosted characteristics are finely adjusted with histopathological data records for cancer detection. Hybrid Inception - ResentV2's architecture is a balance between accuracy and

computational efficiency, making it suitable for complex image classification tasks.

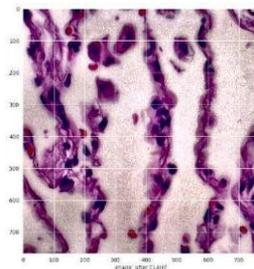
3.6. Architecture

The diagram below 3.4.1 shows a comprehensive, deep learning methodology, de-veloped for lung and colon cancer classification from histopathological images. The pipeline begins with the preparation of images for image processing and LBP (local binary patterns) feature extraction to capture the important texture patterns to be used in the classification. These features are then fed into a tuned inception re-sistance model for training and predictions. The output of the model is evaluated using accuracy, precision, recall, and F1. To allow for interpretability the pipeline considers explanatory AI. Explanatory AI technologies such as Lime and SHAP are used to provide visual clarity to the model by drawing attention to relevant areas of the image and functional contribution. The overall goal of the architecture is to help user achieve a model with high classification accuracy and transparency for clinical diagnostic assistance.

Histopathological Images



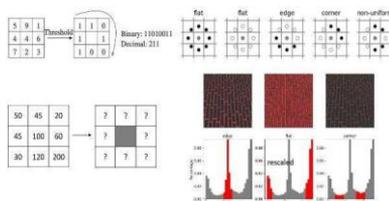
↓
Data Processing



LIME Results

SHAP results

LBP feature



↑ ↑
Evalut on:
 1.Accuracy
 2.Precision
 3.Recall
 4.F1 Score

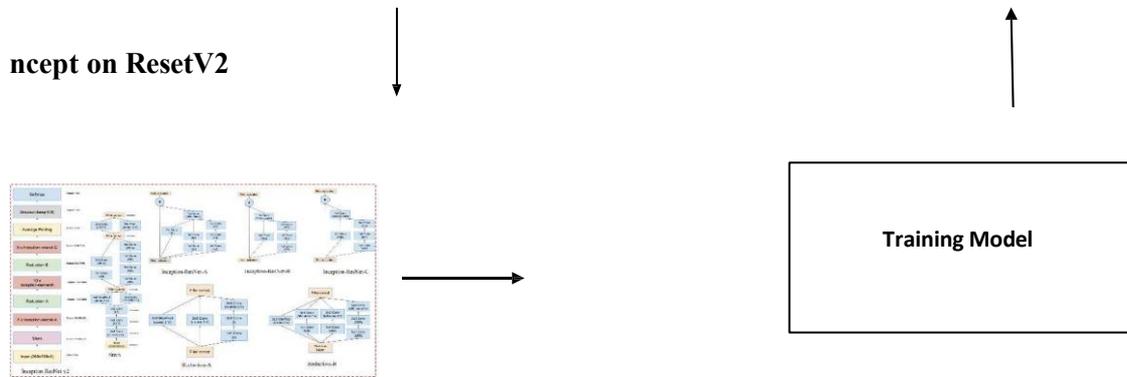


Fig. 1. Architectural diagram of the proposed method of developing steps during step arrows.

3.7. Training and Evaluation

As soon as the model architecture is defined, the following steps concern training and evaluation of the model:

- Model Compilation: This model is compiled using appropriate optimizers (such as Adam) and loss functions (e.g., category crosspieces) to classify them into several classes.
- Training: This model is trained on a training dataset of a certain number of epochs and is used to prevent over-adjustment using techniques such as drops and early stops.
- Evaluation: The trained model is estimated using a test set. Metrics such as accuracy, recall, F1 scores are calculated to evaluate the power of the Model.
- Cross-Validation: K-compartment cross validation can be used.

3.8. Explainability (SHAP and LIME)

System-integrated water-extractable AI technology (XAI) technology is integrated to interpret model predictions:

- SHAP (SHapley Additive exPlanations): SHAP values provide a guaranteed means of incorpo- rating the significance of each feature (or pixel) of the input image in the FI-NAL prediction. SHAP enables a consistent framework for interpreting the outputs of a machine learning model by measuring the significance of each feature of the model's prediction.
- LIME (Local-Interpretable-Modelagnostic-Explanations): LIME aids in taking an interpretive approach to the model to make specific predictions (and understand what aspects influenced the specific predictions). The use of LIME can validate the importance of the proper-ties found in the SHAP and assure that description is consistent. These methods provide transparency in the decision-making process and allow for clinicians to trust and understand model outcomes.

3.9. Final Prediction Output

The final output of the system is a classification label for all input ages, specifying whether the organization is malignant or benign, or is trustworthy. Additionally, an explanatory version of shapes and lime visualizations is provided, highlighting the area of the image, contributing most to the model. This commitment means that the system is accurate and interpreted and will be easier with the introduction of clinics.

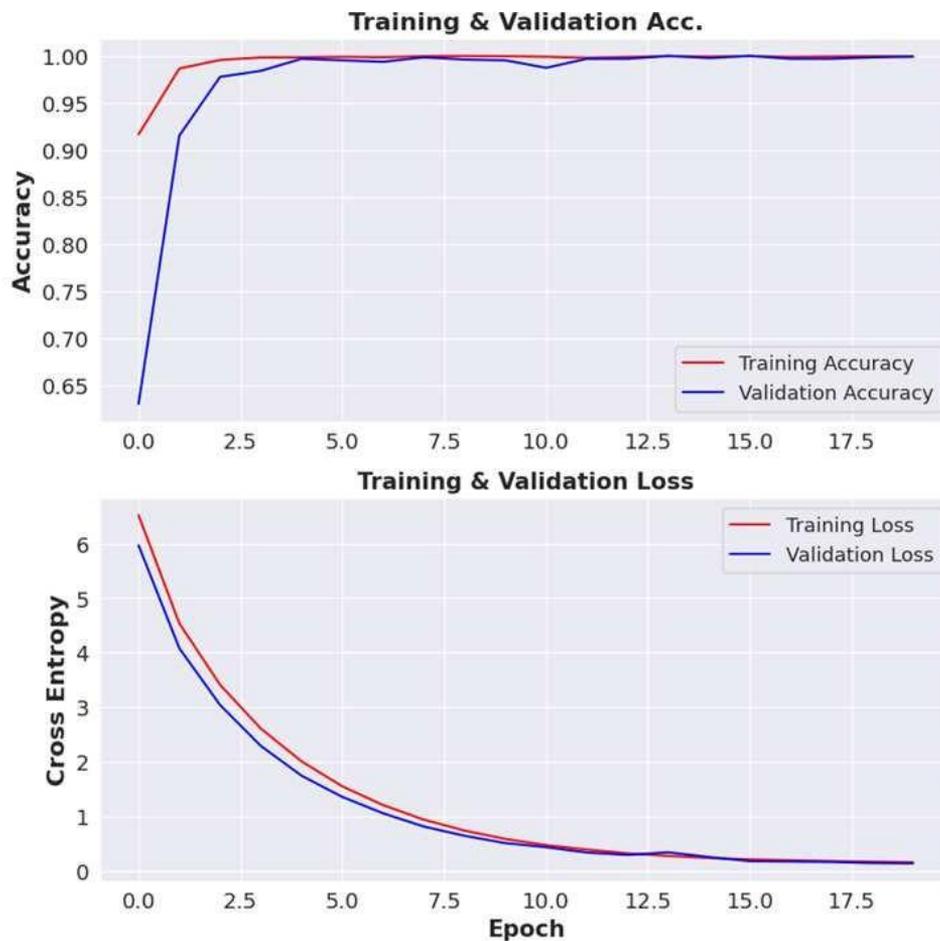
4. Implementation

The proposed approach for lung and colon cancer detection using a deep learning-based system can be implemented through the following steps:

- Environment Setup: Install the required Python libraries and framework conditions such as TensorFlow, Keras, OpenCV, NumPy, SHAP, etc. for deep learning and image processing tasks.
- Dataset Preparation: Download histopathical Image Data Set LC25000. Modify all images with fixed dimensions

suitable for input to the RESETV2 model and process the data.

- Image Augmentation: Use data magnification techniques such as rotation, horizontal/vertical insanity, zoom, and movement to record data and reduce overfitting.
- Feature Extraction: Use local binary patterns (LBP) to extract texture-based features from photographs and improve the model's ability to capture fine-grained patients with tissue samples.
- Model Configuration: Download the educated Inception-Resetv2 model and adapt it for cancer classification. Compile the model: Configure the model with a classification-oriented optimizer and loss function for a multi-class classification problem.
- Compile the model: Set the model using a classification-friendly optimizer and loss function in several classes.
- Train the Model: Split data records for training (80 percent) and test (20 percent) and train models with extended data
- Evaluate the Model: Evaluate the power of the model in the test set and report accuracy and other related metrics.
- Explain Predictions with SHAP: Use (SHapley Additive exPlanations) to interpret model predictions and visualize the contributions of individual characteristics.
- Results Visualization: Visualize the model's predictive and SHAP values to gain insight into the decision-making process.



5. Results

```
labels
colon_aca    5000
colon_n      5000
lung_aca     5000
lung_n       5000
lung_scc     5000
Name: count, dtype: int64
```

Fig. 2. Dataset details

Fig. 3. Pre-processed image

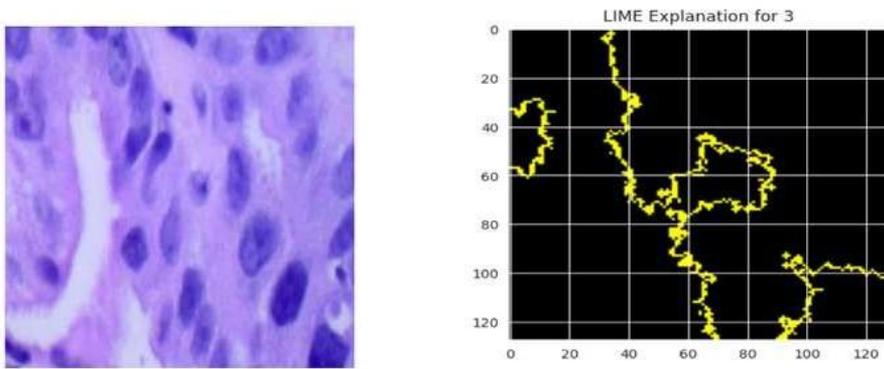


Fig. 4. Lung adenocarcinoma cancer cells detection using LIME

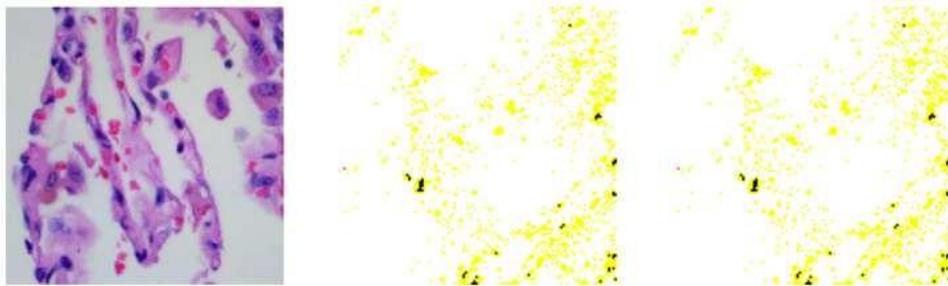


Fig. 5. Lung tissue,cancer cells detection using LIME

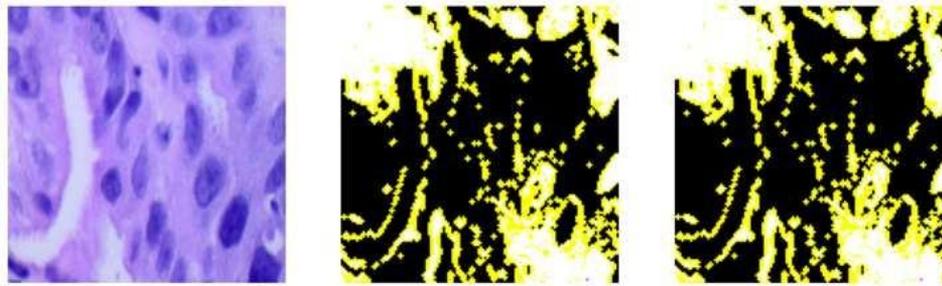


Fig. 6. Lung adenocarcinoma cancer cells detection using LIME

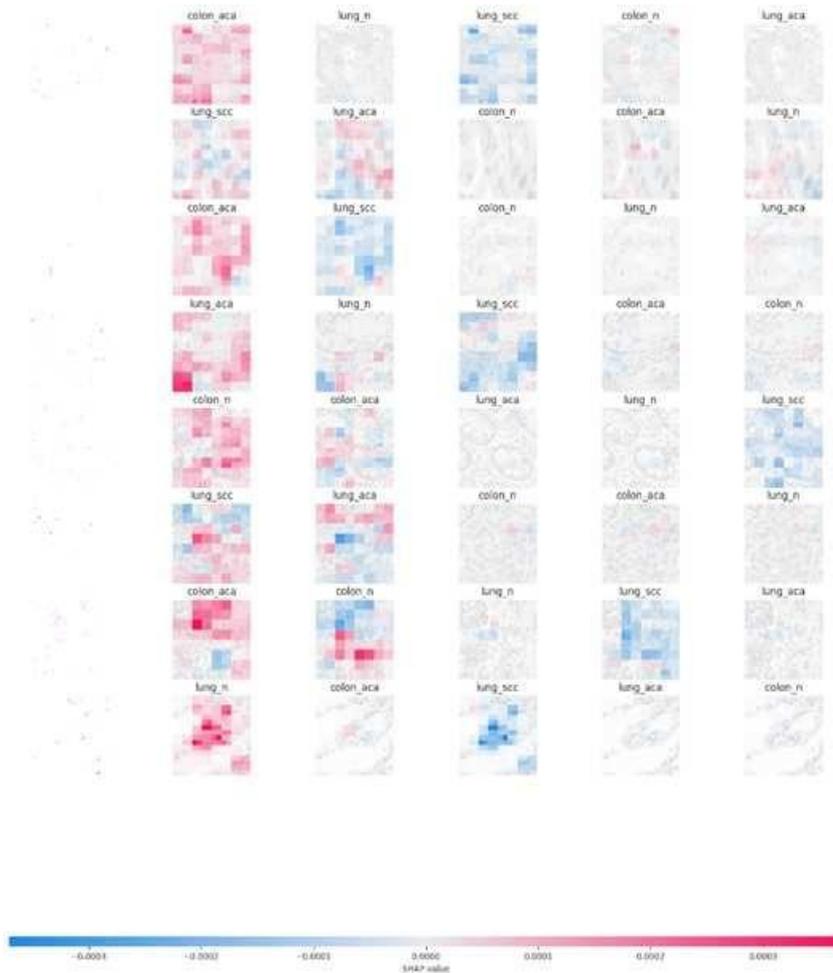


Fig. 7. SHAP results of Lung and Colon sample images

6. Conclusion

In summary, the proposed cancer detection system represents a major advance in the integration of deep learning and distinctive extraction techniques for medical diagnosis. The system captures both very high and texture-specific details from histopathological images by combining the Inception ResnetV2 model with the Local-Binary-Pattern

(LBP) function (LBP) function (LBP).

Accurate detection of lung and colon cancer. The system reaches an impressive accuracy of 99.98 percent and surpasses traditional diagnostic methods based on manual evaluation or basic methods for machine learning. Including described Ki(xai) methods such as shaft and lime adds a critical layer of transparency that allows medical professionals to gain deeper insight into the model decision process. This interpretability addresses key challenges in promoting trust, promoting the adoption of AI into clinical settings, and providing black box models in healthcare systems.

Furthermore, the framework exhibits the advantages of a mixture of powerful characteristic extraction methods, enabling a long-term neuronal network for improved diagnostic reliability and computational efficiency. By bridging the gap between edgeAI technology and real-world clinical settings, the framework provides opportunities to advance the state of the art in cancer detection systems that are less dependent on the user, more accurate and more computationally efficient. Results highlighted the impact AI can have on early cancer detection while opening up patient outcomes and better medical decisions in the long run.

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