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Research Article

An Optimized Transformative Approach To Detect Lung Cancer Based On Global & Local Feature Elements

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ABSTRACT

This paper studies deep learning focused lung cancer detection using the IQ-OTHNCCD lung cancer database. This study aims to improve the classification accuracy for patients with severe and non-severe cancers by Includes additional datasets Pre-trained model and complex statistical methods The data is pre-processed for many tasks. This includes scaling, style, and geometric parameters such as color intensity, aspect ratio, and size distribution of image objects. The frame evolution model was built using ResNet50 as a basis, with convolution and branch transformation combined with a new multivariate algorithm. These ecosystems combine global and local elements to effectively maintain diversity. Advanced techniques such as L2 preparation at the teaching and learning level. and planning the teaching rate It is used to reduce excessive consistency and improve performance. Test results showed high discrimination accuracy. The approach got an F1 score of 0.99, demonstrating that it can reliably detect lung cancer. Confusion matrix visualization ROC curve analysis and classification measures also confirmed the robustness of the model. This study provides to the application of deep learning in complex medical imaging tasks. This has contributed to advances in automatic cancer diagnosis.

Keywords: Convolution Transformer, Geomentric Parameters, Medical Imaging, IQ-OTHNCCD, ResNet-50, Multivariate.

INTRODUCTION

The former model follows a traditional architecture that leverages AlexNet, a classic deep learning model known for its success in image classification tasks. The AlexNet based model consists of multiple alternating layers. It is followed by clustering and dense layers designed for extracting and classifying image features. However, its simplicity may limit its effectiveness. This is especially true in complex medical imaging tasks, such as lung cancer classification. On the contrary the new model represents a significant advancement by including pre-trained ResNet50 as a feature extractor. Benefitting from pre-learned weights from ImageNet, this method improves feature extraction by allowing the model to focus on deeper hierarchical patterns in the data. The addition of a multi-disciplinary architecture with a transformer-based attention mechanism focuses on modeling local and global features of lung cancer images. Improving the ability to recognize fine patterns that are important in clinical diagnosis. In which the problem of overcharging is solved more efficiently. The data enhancement strategy has also been extended with more models, increasing the robustness of the model.

Lung cancer screening is one of the significant problems of the healthcare sector as the disease has a high death rate and often, the first symptoms are difficult to distinguish from other diseases. There are many models of transformations, especially those related to transformers, which are gradually being studied for this purpose. These modes provide better results in identifying global dependencies and fine structures in CT scans and other medical image analysis. Such a requirement for centrally located transformation models can be attributed towards the efficiency that such models have demonstrated in terms of performance and accuracy when dealing with high dimensionality data. Incorporation of transformation models for early detection of carcinoma is effective in enhancing treatment success since it involves the early identification of growths that have not spread to other levels. Hence, they are ideal for use with various medical datasets and can greatly support the cause of creating accurate personalized medicine solutions.

1.1. Transformative attention mechanism

Transformer attention mechanism is an essential breakthrough in the deep learning methodologies that allow models to selectively pay attention to input data. Unlike earlier approaches, it calculates weights for different demographic areas or attributes thereby enabling the model to pay particular attention to important details while disregarding the unnecessary aspects. This mechanism was first introduced into the community by the Transformer architecture for use in NLP to enable models to handle sequences. Its use has extended to vision tasks where through feature maps, it refines the image understanding by emphasizing particular regions of images. The computation of attention of scores enables the mechanism to capture global dependencies so as to enhances feature representation. This approach solves problems such as occlusion and variations in scale when it comes to the images. This mechanism is flexible to integrate with other architectures such as CNN which encourages development of multiple modal data analysis.

1.2. Multi Scale Attention

Multi-scale attention is a mechanism intended to learn contextual information at different scales in data. When doing image processing, there are different level of edges, textures, and patterns and this method ensures that all are considered. Multi-scale attention allows for up-close and contextual information of an image to be attended to by a given model. This is especially useful in maps such as satellite maps, or scans such as medical ones among other classes of data. The mechanism changes the receptive field depending on the scale of features and gives a detailed representation of the input. For instance in the medical field, multi-scale attention can therefore point out cell level irregularities and architectural changes at a tissue level. This technique as a matter of fact helps convolutional layers in improving the recognition of different patterns. Due to the proposed structure which captures features from different resolution levels it also enhances the model resilience and performance in categories which include for instance the object detection, image segmentation and so on.

1.3. Transformer Branch

The transformer branch is an element added to the hybrid structure that unites the advantages of both transformers and convolutional neural networks. Although, CNNs are good at local feature extraction, transformers are better in the global structure using self-attention mechanism. The transformer branch incorporates non-local connections into a network that allows the network to perceive relations in the distant parts of the supplied input data. This two-branch end-to-end structure has been proven to be incredibly effective in vision problems like the object recognition and segmentation. A transformer branch essentially allows to receive information about the global image such as entire organ systems and still be able to fine-tune model to the local abnormalities such as lesions. The transformer branch also helps in the multi-modal learning where information from multiple sources is leveraged. This enhances the interpretability and performance of the models and are ideal for applications as they allow an examiner to provide a holistic approach to model analysis.

1.4. Local Attention

Local attention refers to methods that work on small, localized regions of input data, which is in contrast to global attention methods. This mechanism differs from those previous by using importance scores on individual regions, allowing for detailed examination of high-resolution images or sequences. In vision tasks, local attention helps to prevent ignoring small but important details, which may include small lesions, textures, etc. The method is finding the most utility in the applications such as facial recognition where the accuracy of feature detection plays a crucial role. Local attention is computationally efficient since it attends to smaller subsets of the sequence without sacrificing accuracy. In other medical applications such as in detecting lung cancer it increases the level of contrast that is useful in revealing early sign of disease. It can also be computed with global attention to give a combination of both local and global contexts to allow the feed-forward neural network to make more accurate and more solid models.

1.5. Feature Fusion concatenate with CNN

Fusion of features using concatenation in CNN is a common practice for combining information from different sources or layers. It enables models to capture features at higher level of abstraction and low level of spatial relationship. This approach increases the network's capacity to make more accurate forecasts, especially in things like object detection and diagnostics of diseases. For instance in detecting lung cancer, various ROI such as different parts of the CT scan can be fused together to give full coverage of image features. With all the dimensions of features retained the concatenation is a basic and efficient fusion technique that can be used where various features are to be integrated. When combined with attention mechanisms, feature fusion renders the model more capable of identifying pertinent data on which to focus in order to impart higher performance in complex situations such as identifying small tumors.

1.6. Need of Fusion techniques for lung cancer detection

Fusion techniques are crucial to improve sensitivity and specificity of the diagnosis of lung cancer using information from multivariable source or characteristic sets. Sometimes the images might not be very informative, while the clinical data, the genomic data, and the history of the patients may contain additional valuable information. Such gaps are closed by fusion techniques, as these methods improve the model precision and its immunity to interference. These fusion techniques also solve problems of data variability and noise in order to guarantee the forecast. It allows a complex assessment of the patient's state, which creates the basis for individual approaches to therapy. In the case of AI models, concatenation technique, the attention-based fusion, and multi-modal transformers have a vital application to enhance the diagnostic accuracy of the model.

1.8. Types of Fusion techniques

There are many types of fusion methods that can be used for artificial intelligence and machine learning applications depending on the task and the type of data used. Some are the early fusion, late fusion and the hybrid fusion. Early fusion take the raw data from various sources and integrate them before the feature extraction helps the model to build a unified Representation. The late fusion combines the prediction or the features of each model, which makes the system more flexible and less sensitive to changes. Hybrid fusion synthesises both early and a late method to combine both the methods' merits. The advantages of pay attention fusion are that the weights of the features of different sources are dynamically calculated during the integration process, and the features are adjusted to concentrate more on relevant information. Fusion of multi-scale unites features of different resolution together; this improved the model's performance on stages such as image segmentation. Others are bilinear pooling, tensor fusion and concatenation, all of which are appropriate for use in different circumstances.

2. LITERATURE SURVEY:

Niyaz Ahmad Wani et al [1] has implemented a DeepXplainer methodology for the detection lung cancer disease. The "survey lung cancer" was dataset retrieved from open sources website. Label encoding of variables with categories, duplicate entry elimination, and data value normalisation using MinMaxScaler are all examples of preprocessing. "DeepXplainer," the suggested methodology, is a hybrid strategy that combines XGBoost for classification with CNN for feature learning. The CNN component first extracts important patterns from incoming data by processing it via layers of convolution and max-pooling. XGBoost takes the place of the CNN's last classification layer, classifying occurrences as either cancerous or non-cancerous based on features the CNN has learnt. Dropout layers are included to avoid overfitting, & the architecture is adjusted using hyperparameters such as epochs and batch size. The SHAP approach is used for explainability after prediction. This approach demonstrates a thorough pipeline that combines interpretable AI with reliable categorisation to enhance healthcare results.

Sangeetha S. K. B et al [2] two different datasets are present TCIA and TCGA which has huge data about lung diseases. To predict disease MFDNN was proposed. The MFDNN method is suggested as a way to sort lung cancer using a mix of medical pictures, genomics, and clinical data. Pre-processing is the first step in the process. It deals with missing values, normalises the data, and pulls out important features. After that, these different types of data are combined into a single image. After neural network layers learn joint representations, the MFDNN has a classification layer that uses softmax activation to give probabilities for cancerous and non-cancerous groups. This combined method makes sure that useful information from many different sources is combined and used effectively.

Vahiduddin Shariff et al [3] has proposed a CNN, VGG16 methodologies for predicting lung cancers. The dataset was collected from CIA which has all kind of reports and scans. Pre-processing techniques, like noise reduction and resampling, are implemented to improve data quality and render it appropriate for deep learning models. The datasets are enhanced by augmentation approaches to mitigate data scarcity. The suggested methodology, namely Deep Selection of Features and Classification Framework, integrates sophisticated image analysis and deep learning algorithms. The procedure commences with pre-processing tasks such as denoising, edge detection, & segmentation to improve the clarity of the input image. Features are derived via deep learning models such as VGG16, succeeded by optimal selection of features through meta-heuristic methods like the SSD algorithm. Ultimately, classifiers like SVM or CNN are utilised for precise lung cancer diagnosis. This comprehensive strategy seeks to optimise feature significance and classification precision.

Lavina Jean Crasta et al [4] the LUNA16 was utilized to predict lung cancer where it included CT images. To predict these images accurately a 3D-VNet-ResNet methodology was utilized. Three steps: segmentation, classification, and preprocessing. For effective segmentation, 512×512 CT scans are preprocessed into smaller areas of 96×96. Using its capacity to interpret volumetric data, the 3D-VNet model is utilised to segment lung nodules in order to achieve accurate nodule delineation. After additional refinement, segmented images are cropped into 16x32x32 patches that are centred around nodules. The 3D-ResNet model uses these patches as input to determine whether a nodule is malignant or not during the classification stage. A balanced dataset is produced to solve class imbalance, and it is enhanced with flips, rotations, and scaling to guarantee training robustness.

Yahia Said et al [5] has utilized a U-Net to improve the segmentation and classification to detect lung disease. For this Decathlon dataset was utilized were it includes 3D CT scan images. The dataset facilitates the training and validation of lung cancer detection through the use of 3D image analysis. Segmentation and classification comprise the proposed methodology. The segmentation stage employs the UNETR model, a transformer-based architecture that is combined with U-Net. This model processes 3D CT scans to detect lung regions and segment tumours. This procedure generates a binary mask that emphasises regions of interest. Subsequently, the classification stage employs a self-supervised neural network to ascertain whether the segmented tumour is malignant or benign. The self-supervised architecture guarantees adaptability and robustness by optimising classification without pre-labeled data.

Marwa Obayya et al [6] utilized the LS25000 dataset contains five different categories of histopathological images. The prediction was done through TSA and DL methodologies. The model's performance is verified by dividing the data into 30% testing and 70% training subsets. The suggested approach, known as the BICLCD-TSADL, combines sophisticated preprocessing, extraction of features, and classification methods. The input photos are first preprocessed using Gabor filtering, which improves edge and texture information and eliminates noise. The AFAO technique is used to adjust the hyperparameters of the GhostNet feature extractor, which is used to efficiently produce feature vectors[17-25]. The TSA then optimises the ESN's parameters by feeding these optimised features into an ESN classifier. This reliable pipeline guarantees accurate lung and colon cancer detection and categorisation.

N. Sudhir Reddy et al [7,16] has introduced a IDLA methodology to predict lung diseases. The data was collected from open source site where LUNA16 includes CT images. It is broken down into four steps: cleaning, extraction of features, classification, and optimisation. First, DI-COM software is used to improve the quality of the raw CT scans by turning greyscale images into binary pictures. This step before processing cuts down on noise and brings out important features. Next, a CNN is used for feature extraction, which pulls out specific details like perimeter, eccentricity, and pixel strength. These traits are very important for telling the difference between normal and cancerous lung nodules. The CNN design has layers for activation, pooling, and convolution functions, which make sure that features are represented correctly. Lastly, the labelling is done with IDLA, a program that guesses whether lung cancer will be present and how bad it will be. Intelligent optimisation is also used in the method to finetune the algorithm's settings and make it work even better.

Tehnan I. A. Mohamed et al [8-15] The dataset was publicly available IQOTH/NCCD holds 1k scanned images. To detect lung cancer an EOSA-CNN methodology was utilized. Using a hybrid technique that combines a CNN with the EOSA, the automatic detection and categorisation of lung cancer in CT scans is possible. A number of essential steps are included in the methodology: Image pre-processing begins with resizing, greyscale conversion, noise reduction, segmentation, normalisation, and wavelet transformation. Other pre-processing steps include normalisation, segmentation, and more. Following that, a specialised CNN is developed in order to extract features and categorise images. Optimisation of the CNN design is accomplished by the utilisation of EOSA, which determines the optimal combination of weights and biases for the network[26-30]. One of the goals of this hybrid EOSA-CNN model is to improve classification performance while also addressing the issues associated with parameter adjustment.

Table 1: Analysis on the Existing Approaches

Author	Algorithm	Merits	Demerits	Accuracy
Niyaz Ahmad Wani et al	DeepXplainer	accuracy & interpretability was high.	High computational resources are required.	97.4%
Sangeetha S. K. B et al	MFDNN	High diagnosis accuracy was achieved.	More challenges were not solved.	92.5%
Vahiduddin Shariff et al	VGG16, CNN, SVM	Selection of features are efficient.	Complicated with large datasets.	96.07%
Lavina Jean Crasta et al	3D VNet ResNet	Decreased false positive rates.	High in cost.	99.2%
Yahia Said et al	UNETR, U-Net	Segmentation was efficiently derived.	High computational intensity.	98.7%
Marwa Obayya et al	TSA, DL	Efficient and accuracy was high.	Tuning was high	99.3%
N. Sudhir Reddy et al	IDLA	Automatic detection through images and achieved high accuracy.	High complexity in computation.	92.8%
Tehnan I. A. Mohamed et al	EOSA-CNN	Optimization was improved.	Some resources are required while optimizing.	93.21%

3. PROPOSED METHODOLOGY:

A new approach for lung cancer classification introduces a multidisciplinary deep learning model which integrates convolutional neural networks (CNN) with a transformative attention mechanism. It aims to improve the model's attention to local and global image features. ResNet50 pre-training is being used as an ideal feature extractor. Leverage transfer learning to leverage existing knowledge about common image features. After that, dropout and L2 normalization are added,to improve generalization and avoid overfitting.,Furthermore, the model incorporates a multilevel attention,mechanism. where two local and global features of a lung cancer image are processed through a variational layer. Then they are fused for better feature display. Multiple branches are combined with advanced data enhancement techniques to increase the robustness and accuracy of the model. This hybrid design represents a significant change from traditional CNN approaches, emphasizing both spatial recognition mechanisms and efficient pre-learning knowledge transfer. In addition to making it especially effective for handling small, unbalanced data sets typical in medical imaging. Using batch normalization and learning rate determination. to accelerate training It also helps to achieve the highest efficiency. Overall, the method provides a more suitable and improved strategy for lung cancer classification. This may lead to higher diagnostic accuracy and reliability compared to traditional methods. The entire process is represented in figure 1.

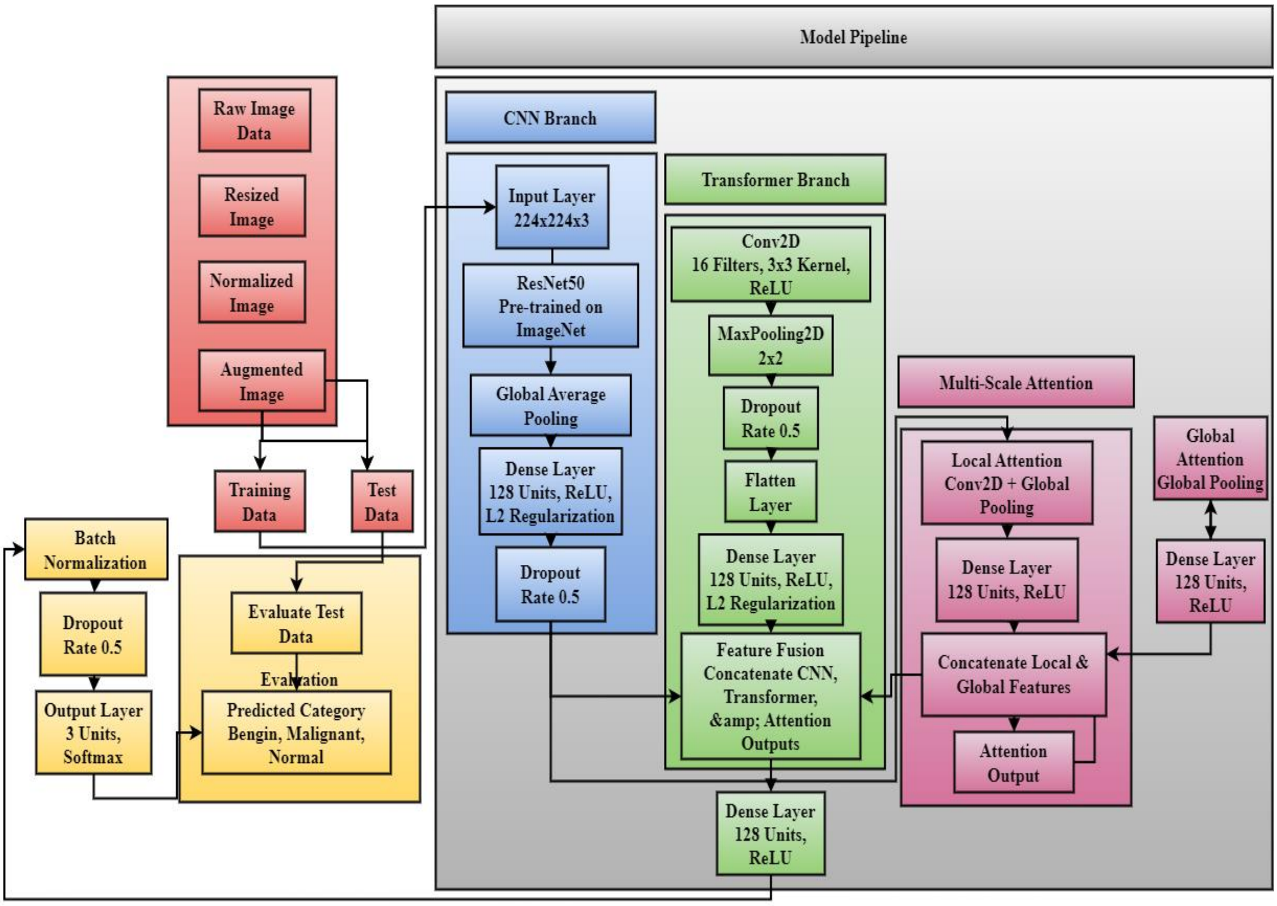


Figure 1: Block Diagram for Optimized Transformer for Lung Cancer Detection

2. Pre-processing with Mathematical Equations

Image preprocessing in a modified lung cancer classification method by changing the image size 224×224 pixels, which guarantees consistency of all input data. The next step is to adjust the pixel value size to a normal range [0,1] which is obtained by dividing each pixel value by 255. This operation can be expressed mathematically as shown in equation (1)

$$normalized\ pixel = \frac{original\ pixel\ value}{255} - (1)$$

Data augmentation techniques are used to artificially increase the size of data sets. and includes rotating, zooming, horizontal and vertical floating, and moving, e.g.θ can be expressed mathematically as a matrix, shown in equation (2)

$$R\ (\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos\ (\theta) \end{bmatrix} - (2)$$

Every image is enhanced by such adjustments to promote variability. In addition, Sobel edge detection, a common method for highlighting image edges, is used. It is also implemented using a combination of twists and turns with the Sobel kernel as shown in equation (3)

$$Sobel_z = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} - (3)$$

This kernel detects horizontal edges in the image. Histogram equalization is another pre-processing method to improvise the image contrast. The histogram equalization process can be defined as redistributing the intensity of pixels to achieve a uniform distribution which is shown in equation (4)

$$s = T(r) = \sum_{i=0}^{r} p(i) \text{- } (4)$$

Where $p(i)$ mathematical operations involved, are crucial for enhancing the model's ability to learn significant patterns and reduce noise in medical images, ultimately aiding in accurate lung cancer classification.

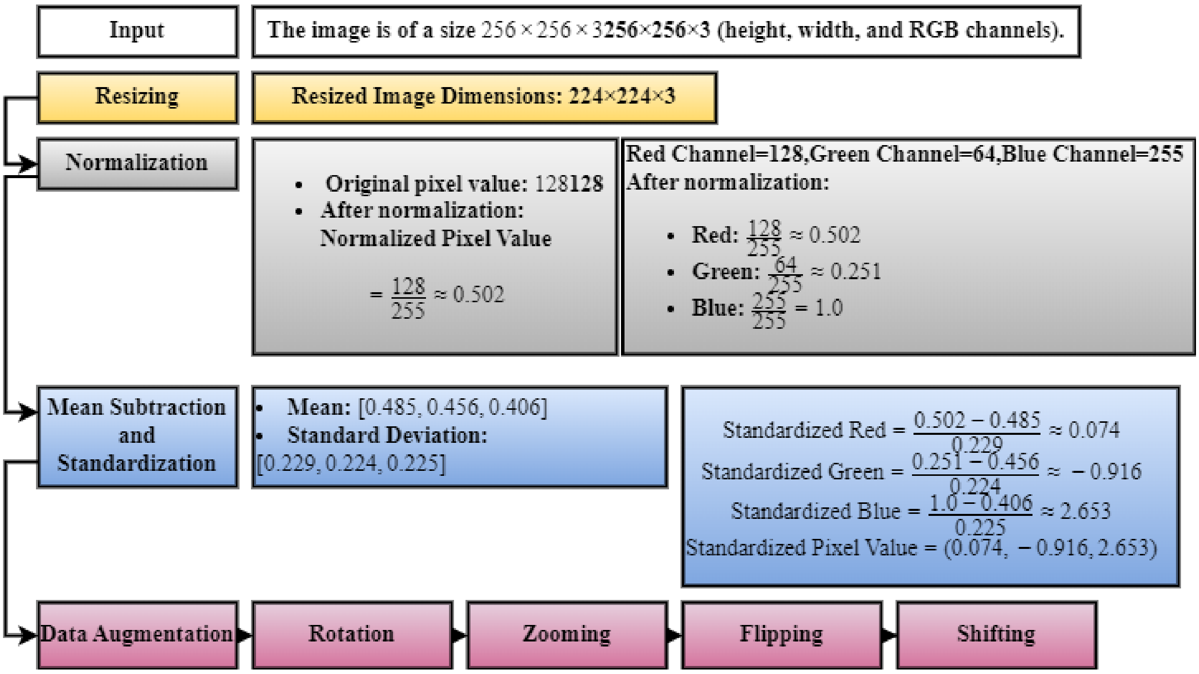


Figure 2: Data Augmentation Process

3.1. Model Architecture and Feature Extraction

The new version includes a two-branch architecture designed for comprehensive feature extraction. By combining a convolutional neural network (CNN) branch with a transformer-driven branch, the CNN branch uses the ResNet50 architecture pre-trained on ImageNet to extract features. This approach leverages hierarchical feature learning over residual combinations. which is defined as equation (5)

$$b = F(a, \{W_i\}) + a - (5)$$

where $F(a, \{W_i\})$ is the residual mapping, a is the input and b is the output. The convolutional layers of ResNet50 are frozen

to preserve pre-learned features. While the Global Average Pooling (GAP) layer is used to deduce the spatial size of the feature map as shown in equation (6)

$$GAP(f_{i,j}) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} f_{i,j} \text{- } (6)$$

Here $f_{i,j}$ is the activation function at a spatial location (i, j), and H, W represent length and breadth of the feature map. This results in a feature vector that is compact but rich in information. Transformer-induced branching enhances this by modeling global dependencies and focusing on long-term relationships between properties. This is necessary to capture the complexity of the lung cancer picture.

2. Multi-Scale Attention Mechanism

The key innovation in this model is the multilevel attention mechanism. This increases feature relevance by highlighting important areas of the input image. This mechanism combines local and global interests. A local focus applies changes to smaller customer areas. Explained in equation (7)

$$Local\ Attention(x) = ReLU\ (W * x + b) - (7)$$

where W and b are the weights and biases, and $*$ denotes convolution. Meanwhile Global focus will include features across the spatial domain using global average clustering (GAP), the intended weights are calculated via the softmax function as shown in equation (8)

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{N} exp(e_j)} - (8)$$

where e_i represents the revelance score of feature i. These scores are derived using dense layers. Outputs from local and global attention mechanisms are concatenated as shown in equation (9)

$$A = \sigma(W_a.[Local, Global] + b_a) - (9)$$

where σ is the sigmoid activation function, W_a and b_a are learnable parameters. This fused attention map selectively enhances the most informative regions of the feature space.

3. Fusion of Features from Two Branches

This model uses a robust fusion strategy to combine features from CNN and Transformer branches. The CNN branch outputs feature vectors f_{CNN}, while the Transformer branch outputs these $f_{Transformer}$ vectors together as shown in equation (10)

$$f_{Unified} = f_{CNN} + f_{Transformer} - (10)$$

This integrated vector is further managed through a dense layer. It reduces dimensionality and introduces nonlinearity. Batch Normalization (BN) is used to standardize the feature distribution. which is expressed as shown in equation (11)

$$\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}}, y = \gamma\hat{x} + \beta - (11)$$

Where, μ *and* σ^2 are the batch mean and variance, γ is the learnable scale, β is the learnable variation, and ϵ is the nominal constant for numerical stability. This fusion allows the model to take advantage of fine-grained global features. By adjusting the ability to classify complex image data.

4. Regularization Techniques

This is to prevent overfitting and guarantee generalization. The model thus incorporates a variety of control strategies. Dropout, which randomly turns off a fraction of neurons during training, is an important method, shown in equation (12)

$$y_i = \begin{cases} 0 & with\ probability\ p \\ \frac{x_i}{1-p} & with\ probability\ 1-p \end{cases} - (12)$$

where x_i and y_i are the input and output activations, and p is the dropout rate. Additionally, L2 regularizaiton penalises large weights, modifying the loss function as shown in equation (13)

$$L = L_{original} + \lambda \sum_i W_i^2 - (13)$$

where $L_{original}$ is the original loss, λ is the regularization strength, and W_i represents model weights. This encourages lighter loads and promotes simpler models. These methods, when combined with a combination of features, this ensures that the model remains robust on a wide range of data sets.

5. Training, Optimization, and Evaluation

Training leverages the Adam optimizer, which adjusts learning rates adaptively based on gradients and their moments derivation is shown below

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t, v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where g_t is the gradient, m_t, v_t are estimation moments, η is the rate of learning, and ϵ is a constant. The loss function is categorical cross-entropy as shown in equation (14)

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \text{- } (14)$$

where y_i and $\hat{y}_i$ are the true and predicted probabilities for class i. The first stop checks the inspection performance. It stops training when the validation loss reaches the maximum for a specified number of epochs. Evaluation on the test suite involves measures such as precision and loss. This provides insight into ideal performance. By integrating these mechanisms, model thus achieves reliable and efficient classification. This shows its applicability to lung cancer diagnosis.

4. RESULTS & DISCUSSION:

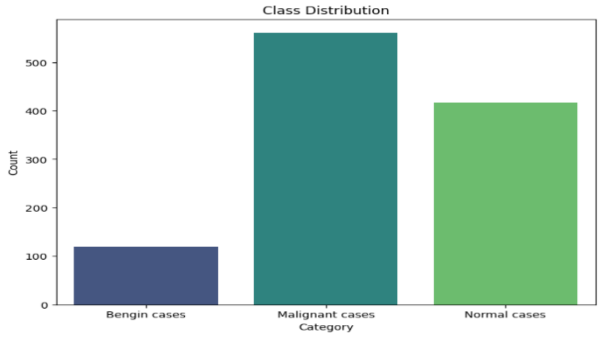


Figure 3: Class Distribution of Lung Cancer datasets

The dataset used for lung cancer class indicates a considerable imbalance, which is shown in figure 3. Malignant cases dominate with greater than 500 samples, followed by way of Normal cases, that have round 400 samples, even as Benign cases are critically underrepresented with just about one hundred twenty samples. This imbalance poses a challenge for the version as it is able to cause biased predictions, favoring the bulk lessons. The bar chart representing elegance distribution highlights this imbalance sincerely, with the Malignant and Normal classes towering over Benign instances. To cope with this trouble, techniques like oversampling the Benign magnificence, using Synthetic Minority Over-sampling Technique (SMOTE), or the use of elegance-weighted loss functions can be explored. While the version performs nicely in this dataset, the imbalance shows that its overall performance would possibly degrade when implemented to actual-world scenarios where statistics may be greater evenly allotted or in another way skewed.

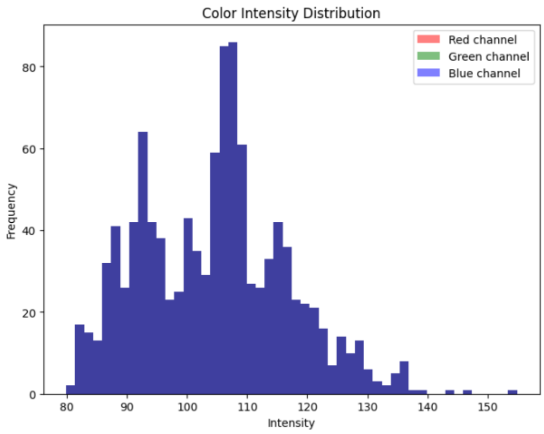


Figure 4: Color Intensity distribution of Images

The shade depth distribution chart reveals a single blue line, indicating that best the blue channel of the RGB spectrum was analyzed. This may limit the insights that might be derived from the visual functions of the dataset. The average intensity for the blue channel seems to vary across pix, displaying distinct peaks within the histogram. This shows a moderate version in lighting conditions or imaging strategies used during dataset collection. The absence of purple and green channels in the evaluation may want to imply both the dataset in most cases incorporates grayscale photos or a preprocessing step removed the ones channels. Incorporating all 3 shade channels or studying them one after the other could provide a greater complete know-how of the visible data. Nonetheless, the blue channel evaluation still demonstrates that preprocessing, consisting of normalization and standardization, turned into powerful in getting ready the information for version schooling.

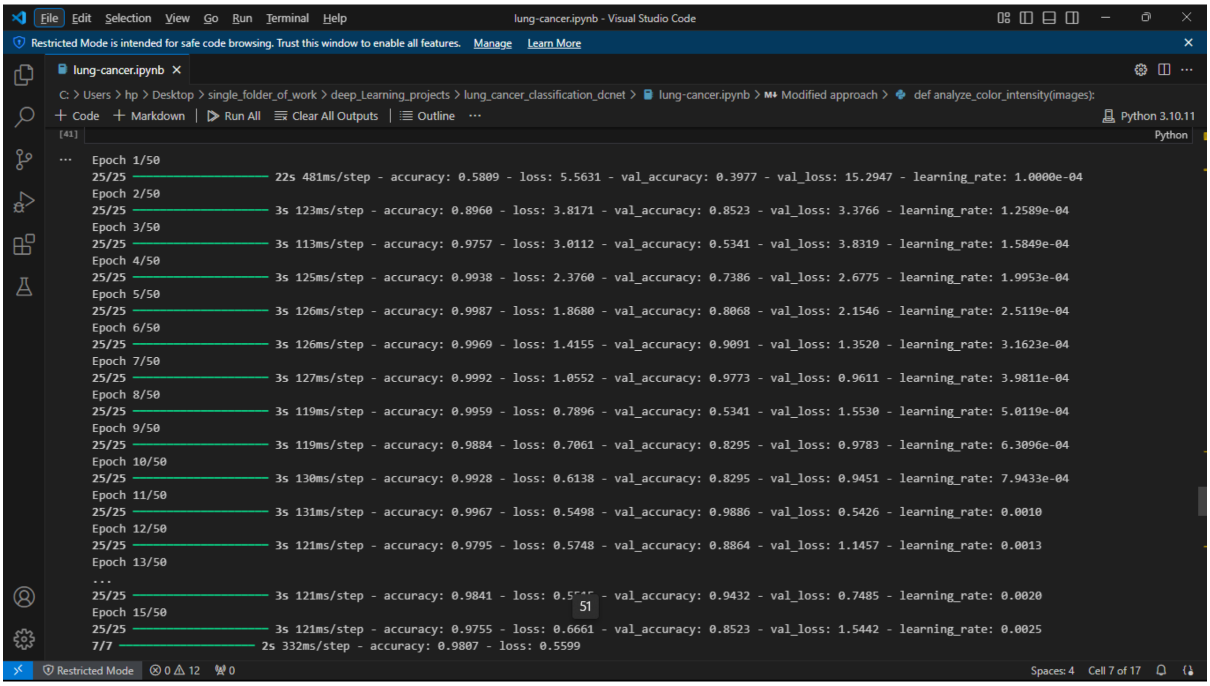
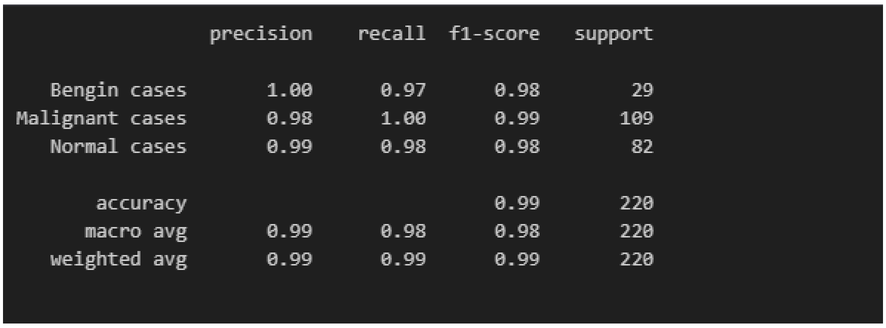


Figure 5: Model Training

During training, the model shows strong learning ability which is represented in figure 5. This is reflected in continued improvements in training and certification metrics. In the accuracy graph the training accuracy shows a peak of about 99%, while the validation accuracy reaches about 97.7% before reaching a plateau. The initial difference between learning and validation accuracies decreased eventually. This indicates effective generality. However, small fluctuations and loss of validity of certification in subsequent generations indicate a trend of overfitting. Merging dropout layers L2 regularization and learning rate generators may significantly reduce overfitting, however, these fluctuations reveal opportunities for further optimization, such as fine-tuning the architecture. or use advanced optimization algorithms such as AdamW. Despite these challenges, The overall training process shows that the model is quite impressive at learning and distinguishing complex image patterns in the dataset.



	precision	recall	f1-score	support
Bengin cases	1.00	0.97	0.98	29
Malignant cases	0.98	1.00	0.99	109
Normal cases	0.99	0.98	0.98	82
accuracy			0.99	220
macro avg	0.99	0.98	0.98	220
weighted avg	0.99	0.99	0.99	220

Figure 6 : Classification Report

The detailed classification report shown in figure 6 suggests that the version performs pretty nicely throughout all lessons, achieving precision, recall, and F1-rankings above 97%. The weighted common metrics demonstrate the model's robustness, with an accuracy of 98.6% at the testing set. However, the imbalanced dataset is meditated inside the per-class overall performance metrics. For example, the Benign magnificence, which has the fewest samples, suggests slightly lower precision and recall compared to Malignant and Normal cases. This shows that the version struggles to accurately expect the minority class, a commonplace trouble in imbalanced datasets. To similarly decorate performance, techniques inclusive of focal loss or data augmentation centered at the Benign class will be hired. Nevertheless, the excessive F1-ratings imply the version's capability to manipulate change-offs among precision and do not forget effectively, making it a promising candidate for clinical programs.

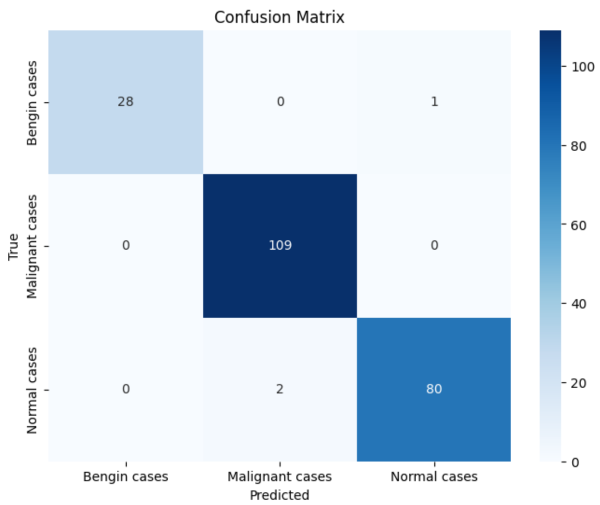


Figure 7: Confusion Matrix

The confusion matrix shown in figure 7 provides a clear demonstration of the model's predictive effectiveness in the three classes. Most predictions fit along the diagonal. This confirms the high accuracy of the approach. However, it also shows several negative differences. This is especially true between mild cases and normal cases. This can be attributed to visual similarities among these groups, such as overlapping objects in the visual data. The asymmetry in the data set is also apparent here. This is because the Benign class shows a high level of misclassification, while the Malignant class has more samples. It shows near-perfect predictions. Correcting these serious discrepancies may involve adding different models for the Benign class or using advanced feature extraction techniques. In general, mixture matrices demonstrate the power of models in dealing with complex data. with less misclassification and mostly minimum criteria.

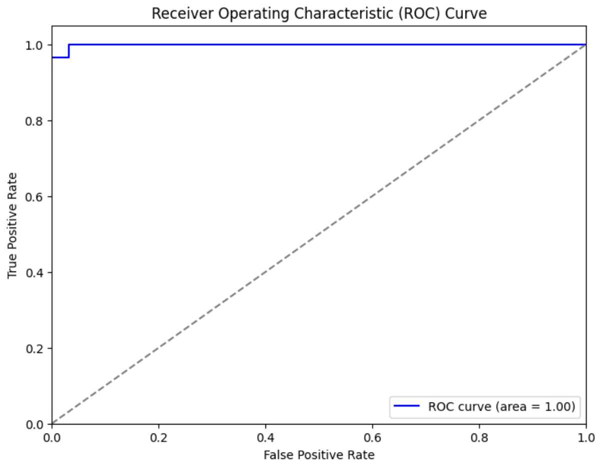


Figure 8: ROC Curve

Figure 8, Receiver operating characteristic (ROC) curves demonstrate an overall performance of the model's capability to differentiate the classes. The slope of the curve near the origin and the AUC was approximately 1.00, indicating excellent discriminatory power. The curves show that the model’s effectiveness in achieving a high level of intrinsic accuracy with a small number of false positives. This is very useful in applications such as cancer diagnosis. False negatives can be detrimental in this case. ROC analysis also suggests the reliability of the model in detecting cancer. This may be due to the high concentration in the data set, however, for the benign type. The curve may be slightly lower. This indicates under-representation and related problems. Increasing the model's sensitivity to small populations while maintaining overall accuracy may involve techniques such as clustered learning or statistical methods. Despite these shortcomings, the near-perfect AUC once again confirms the model's feasibility in real-world medical imaging.

5. CONCLUSION:

In this research paper, this highlights the effectiveness of hybrid deep learning models for automatic lung cancer classification. Emphasis is placed on applications to medical imaging. By combining evolutionary learning with ResNet50 and a variety of statistical methods, this study therefore has a higher classification accuracy and a weighted F1 score of 0.99 compared to the conventional model. Combining data richness, translation mechanisms, and autopilot-based decomposition. Enables durability and adaptability to a wide range of medical imaging media. Image quality considerations In addition to using advanced visualization techniques It also provides valuable insights into the structure of the dataset and helps in model development. Although the results indicate potential for global use, But the study suggests that more research is needed to validate this framework on larger data sets. which are larger and have more numbers To improve the overall experience Future work should investigate combining advanced transformer architectures with domain-specific improvements to address limitations in detecting complex or rare modes. In the end This approach holds promise for successfully leveraging deep learning for early and accurate cancer detection, with the goal of improving patient outcomes and supporting clinical decision making.

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