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Lung Cancer Detection using a Hybridized Contrast-based Xception Model on Image Data: A Pilot Study

Joy Agboi[1], Paul Avwerosuo Onoma[2*], Eferhire Valentine Ugbotu[3], Tabitha Chukwudi Aghaunor[4], Chris Chukwufunaya Odiakaose[5], Arnold Adim Ojugo[2*], Andrew Okonji Eboka[6], Amaka Patience Binitie[6], Peace Oguguo Ezzeh[6], Patrick Ogholuwarami Ejeh[5], Victor Ochuko Geteloma[2], Rebecca Okeoghene Idama[5], Anderson Ise Orobor[2], Chris Chukwudi Onochie[6], and Chris Obaro Obruche[7]

[1] Delta State University, Abraka, Delta State 330105, Nigeria. agboijoy0@gmail.com
[2] Federal University of Petroleum Resources Effurun, Delta State 330102, Nigeria. kenbridge14@gmail.com, ojugo.arnold@fupre.edu.ng, geteloma.victor@fupre.edu.ng, orobor.anderson@fupre.edu.ng
[3] University of Salford, Manchester M5 4WT, United Kingdom. eferhire.ugbotu@gmail.com
[4] Robert Morris University, Pittsburgh, PA15108, United States. tabitha.aughaunor@gmail.com
[5] Dennis Osadebay University, Asaba, Delta State 320212, Nigeria. osegalaxy@gmail.com, patrick.ejeh@dou.edu.ng, emordi.frances@dou.edu.ng
[6] Federal College of Education Technical, Asaba, Delta State 320212, Nigeria. ebokaandrew@gmail.com, amaka.binitie@fcetasaba.edu.ng, esther.ogboru@fcetasaba.edu.ng, xtoline2@gmail.com
[7] Southern Delta University, Ozoro, Delta State 330103, Nigeria. obrucheco@dsust.edu.ng
* Correspondence: kenbridge14@gmail.com; ojugo.arnold@fupre.edu.ng

Abstract: Lung cancer has since become the second largest direct cause of death when compared to other forms of cancer. Lung cancer is easily diagnosed via medical x-rays, MRIs and CT-scans. The use of learning schemes in identification of disease has become a veritable tool in medical frontiers. But, a major challenge with image classification – is attributed to the disease severity, and model's ability to address feature enhancements in model designs for image processing. The models must capture intrinsic features with image enhancements in regions of interest – amongst other feats. Our study uses a median filter (AMF) with contrast enhancement (CLAHE) to normalize images, use a variation-mode decomposition as preprocessor to sustain multimodal image learning upheld by the Xception model. VMD handles complex image data to resolve mode mixing in its AMF and CLAHE. This is further upheld via localized context and hierarchical image representation in our CNN-based Xception model to yield improved training efficiency, model stability and generalization even with complex spatiotemporal dependencies inherent the image dataset. Our result shows the proposed method performs well in lung cancer detection, with significantly enhanced time convergence and reliability to yield a 1.000 Accuracy, 0.994 Precision, 0.989 Recall and 0.989 F1-score. Thus, the proposed model provides an effective image recognition and detection solution for lung cancer.

Keywords: Lung cancer, Xception model, CNN, image recognition, image processing

1. Introduction

The World Health Organization in 2018 named lung cancer as the second deadliest diseases [1], directly responsible for over 1.76 million patient death globally [2]. This is because the cells within a body, have particular functions with fixed life cycle [3]. While, the apoptosis – the inevitable death of cell naturally occurs [4], new cells are created to immediately replace dead cells, and ensure normal body functioning [5]. Dead cells often fester within the tissue to cause cancer since they lack the ability to die [6]; And also use up and usurp the body resources meant for healthy cells [7]. Cancerous cells often metastasize as tumors to hamper the production of antigens and white blood cells [8]; Thus, degrades the performance of a body's immune [9] – causing deviations that prevents optimal body functioning [10], [11]. Medical imaging as a critical factor in modern medicine – provides clinicians with vital data needed for diagnosis, treatment, and monitor of patients with cancerous diseases [12]. As a non-invasive procedure, medical image yields a visual position of a body's tissues and internal

organs. Traditional image analysis was previously hinged on a czars skillset, which was highly prone to error(s) and misdiagnosis [13], [14].

The consequent adoption of machine learning (ML) and deep learning (DL) for the identification cum classification of medical images continues to witness huge success [15]. And, image recognition has increasingly become an effective tool in electronic healthcare delivery for detection of cancerous cells via x-ray images [16]. ML schemes have been widely adopted to process, analyze and classify images of lung cancer to identify signs associated with the lung cancer disease, more quickly and accurately [17]. However, many ML schemes explore feature-shape-color extraction prior classifying the image – with the most widely used as the Gray level co-occurrence matrices [18]. Common ML used includes Random Forest [19], Logistic Regression [20], XGBoost [21], [22], Neural Net [23], [24], and Support Vector Machine [25], [26]. With ML quickly replaced by DL especially in image analysis – DLs have provisioned enhanced generalization [27] and classification. Convolution neural network (CNN) as a frontier DL scheme – has unveiled improved accuracy over ML schemes [28], [29]. It has now become a veritable technique for image analysis for object classification via extracted features [30]. CNN recognizes image data via its convolution layers as they are designed to learn intricate patterns from even small dataset unlike the ML schemes. They have been known to capture relevant features, and transmit the learned knowledge from one task to a related task via its pre-trained model [31]. This feature is known as transfer learning paradigm [32], [33].

A major merit of CNN over ML – is in its capability to automatically extract complex patterns from image dataset without its need for a separate feature extraction [34], [35]; And thus, provisions an enhanced hierarchical representation of the image from a local context as applied to lung cancer detection. Additionally, its transfer learning capability allows learning with improved generalization even for small/large datasets [36], [37] – making it an adaptive, intelligent choice to handle the spatial and structural complexity in image data for lung cancer diseases. Sample variants for the CNN model used in both scenario with large/small dataset includes: (a) VGG – an easy-to-implement, symmetric model [38], (b) EfficientNet adopts few features to yield improved performance [39], (c) MobileNet – yields improved efficiency via its depthwise separable convolution to reduce process load in mobile devices [40], (d) DenseNet – uses its highly connected layers to overcome knowledge loss [41], [42], and (e) ResNet – uses its residual blocks to train and improve ground truth for very deep networks without degraded performance [43], [44].

This study explores the Xception architecture – which though similar to the EfficientNet, yields improved generalization efficiency with superior performance in both small/large dataset scenarios especially for transfer learning scenarios [45], [46]. Thus, we deploy Xception model for lung cancer recognition due to its ease of implementation, its ability to utilize both small and large dataset, and for its optimal performance [47]. The study contributes as thus: (a) understudy previous works to glean insight into DL schemes that will efficiently identify lung cancer diseases [48], [49], (b) train the Xception model to capture to adequately capture predictors to lung cancer [50], and (c) evaluate model with known metrics like recall, precision, and F1 against known benchmarks [51], [52].

2. Experiment: Materials and Methods

Chest x-rays with displayed lung sections have since become a cost-effective, most frequently exercised used medical image examination. X-ray images as utilized in clinical diagnosis can be quite challenging. Though readily available – its lack of large publicly available image-set with annotations to achieve clinically-relevant aided-diagnosis (CAD), makes it difficult to be implemented in both ML and DL schemes. A major hurdle to create and acquire large X-ray image-set can be attributed to the shortage of resources for labeling such images. Thus, we adopt the proposed methodology as in Figure 1 as detailed in the following steps:

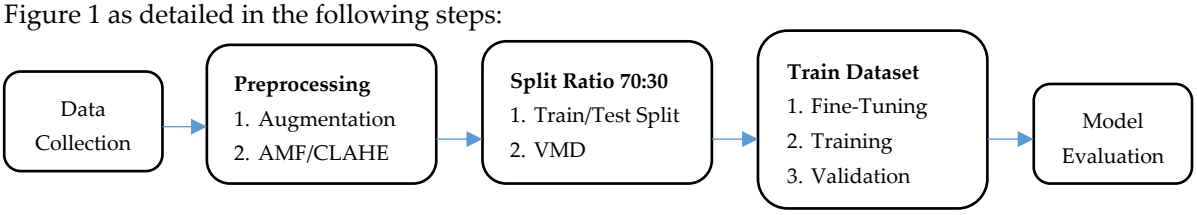


Figure 1. Proposed Lung Cancer Detection Methodology

Step-1 – Data Collected: We use the National Institutes of Health (NIH) dataset as available [web]: kaggle.com/datasets/nih-chest-xrays/data [53] that consists of 112,120 recorded X-ray images with an overlapped 6,511 images in the corpus as captured from 30,805 unique patients as in the Figure 2.

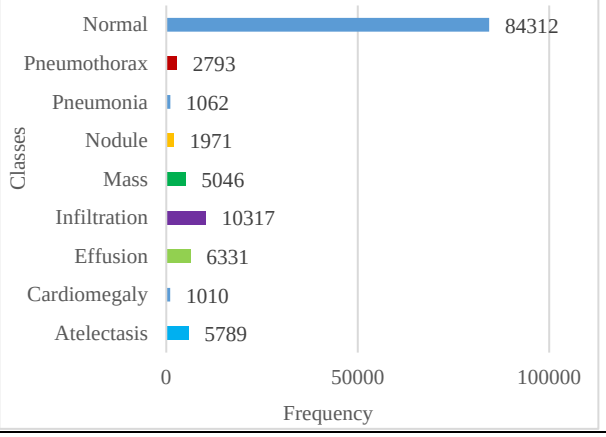


Figure 2. Original NIH dataset with 9-classes

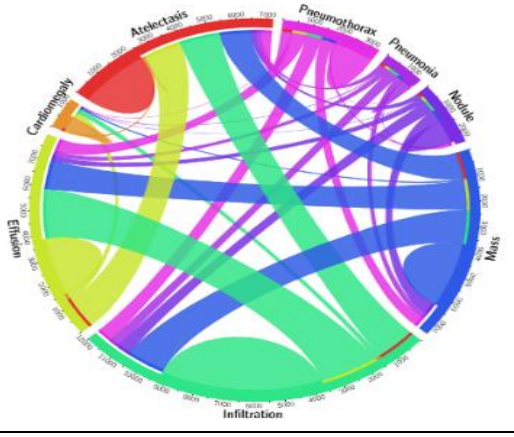


Figure 2b. Label co-occurrence

Step 2 – Preprocessing cleans up a dataset by expunging all duplicates to ensure dataset integrity, and removes missing records to ensure quality [54] – to yield an optimized data. Images were resized via RGB-form as 5124×5124×256 image dimension [55], [56] using the Gray level color. Denoising seeks to removes noise while conserving the image edges – achieved as below:

- ✓ Augmentation is used to increase image diversity so that an optimal training process is produced [57], [58] via techniques such as rotation, flip, and image enlargement.
- ✓ Adaptive Median Filter: Images are often corrupted due to presence of Gaussian noise as well as salt-and-pepper noise. Filters are used to often restore image intensity to about 20% to enable the explored model efficiently identify cases properly. Median filters effectively remove noise by replacing its gray-level for each pixel with the computed (neighborhood) median value of the x-ray image [59]. Our explored adaptive median filter overcomes the challenges of the median filter as thus: (a) finds the median value for a kernel [60], and (b) assess whether the current pixel value is an impulse (salt-and-pepper noise) – so that, if a pixel value is corrupted, it retains the median [61]; Else, it retains the gray-level scale pixel value. Thus, this ensures that only the pixels with impulse noise is swapped, while all other pixel values are retained as they are. Thus, it extends this capability so as not to erode away edges or small details in the image [62], [63].
- ✓ Enhancements has two (2) goals namely to improve the appearance for visual interpretation, and to improve the performance of other tasks such as the image analysis, object detection, and image segmentation [64]. We utilize the contrast limited adaptive histogram equalization (CLAHE) to normalize the x-ray images. Its resolves the over-amplification of noise in contrasted x-ray using 2-crucial feats (clipLimit and tileGridSize). CLAHE is done as follows [65], [66]: (a) input image is divided into smaller, non-overlapping tiles or regions, (b) histogram computation for each tile to show the intensity distribution within that region, (c) apply histogram equalization to enhance the contrasts of each tile to increase the contrast, (d) to avoid noise over-amplification, histograms are clipped to limit the number of pixel values that can be amplified, and (e) to avoid the abrupt transitions at tile boundaries, enhanced tiles are interpolated to create the final output image [67].

Step-3 – Split-Decompose-Normalize: The explored dataset is first split into train (75%) and test-set (25%). The train-set was normalized using a variation mode decomposition [68] that decomposes image(s) into several intrinsic mode functions [69], and extracting data about a defined Euclidean center to minimize errors between its input and sum of the modes (optimization). Its distinctly keeps each image-mode separate, while resolving the complex chaotic, non-stationary nature of the dataset [70] to ensure dataset suitability for image decomposition. With its high-threshold resistance to strong noise – decomposition is performed using Equation 1 with u_k as k-modal component, ω_k is k-central spatial form, $\delta(t)$ is Dirac delta function, t is operation in gradient descent, and f is input

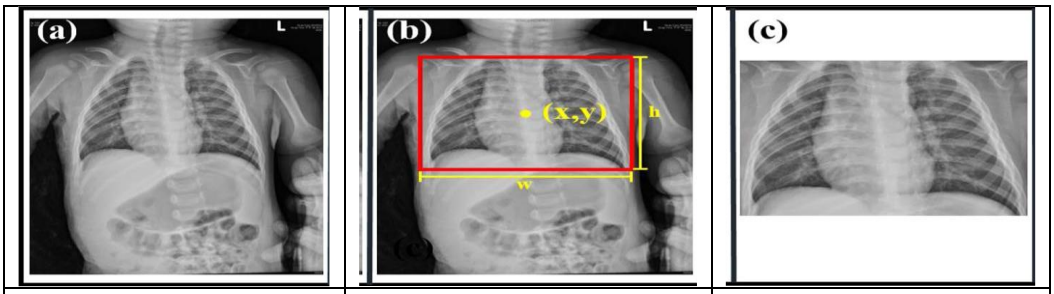
sequence [24]. Equation 1 incorporates a penalty factor α with its Lagrange multiplier that adjusts all original constraint conditions.

$$L = \alpha \sum_{k} ||\partial_t[(\delta(t) + j\frac{1}{\pi t})^* u_k(t)]e^{-j\omega_k t}||_2^2 + ||f(t) - \sum_{k} u_k(t)||_2^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \quad Equation\ 1$$

Step-4: Model Construction, Training and Validation: We use the Xception transfer learning model. As a DL scheme – it utilizes split convolution to separate its spatial convolution to yield improved computational efficiency [72] that leads to reduced predictors used in model construction for ground-truth. Table 1 shows model configuration – and our Xception scheme effectively extracts complex image feature representations; while, using its transfer learning ability as an effective tool for image processing especially in cases where limited resources is a critical factor. We tune the model with an external dataset to adequately adjust the model weights about the target data using a target class of nine (9). Conversely, the last output layer is replaced to correspond with the number of target classes. Additionally, we use several hyperparameters described in Table 1.

Table 1. Xception Model Configuration with Hyper-parameter Settings

Features	Output shape	Param#
Xception (functional)	(None, 7, 7, 2048)	20861480
Flatten_4 (flatten)	(None, 100352)	0
dense_12 (dense)	(None, 64)	6422592
dense_13 (dense)	(None, 32)	2560
dense_14 (dense)	(None, 9)	256
Hyper-parameters	**Settings**	
epochs	10	
batch_size	64	
seed	56	
TF_seed	768	
loss	if keras.losses.CategoricalCrossentropy(label_smoothing=0.0001)	
optimizer	if keras.optimizers_Adam(learning_rate=0.0001)	



a. original x-ray image | b. location bounding box | c. image cropped by box

Figure 3. Segmented Region of Interest from original-to-cropped images

Step-5: Model Evaluation: Note that with training-and-validation processes, we wish to measure their accuracy and loss. The extent to which a model correctly identifies data about the target class is termed accuracy – which in Keras context is the number of correct predictions divided by the total samples. Conversely, loss assesses how well the model generalizes about the target value. Thus, the goal is to optimize the model to effectively reduce its loss values via its categorical cross-entropy for multiclass identification, affirmed by recall, precision and F1-Score as in Equations 2 – 4 respectively.

$$Recall = \frac{TP}{TP + TN} \quad Equation\ 2$$

$$Precission = \frac{TP}{TP + FP} \quad Equation\ 3$$

$$F1 = \frac{2 \times Precission \times Recall}{Precission + Recall} \quad Equation\ 4$$

3. Results Findings

3.1. Performance Evaluation

With dataset split resulting into training 70% (83042-images), and testing 30% (35589-images) – the Table 2 shows our proposed model yields an Accuracy of 1.000 to outperform known CNN-based models used. Figure 4 shows both training-and-validation accuracy and loss plots. For the training-and-validation accuracy plot – the proposed model witnesses a steady rise from 0.845 in its second epoch, to 0.998 at its 52nd epoch. Conversely – with this significant learning at training, the proposed model in addition yields a sharp decrease in its training-and-validation loss from 0.236 also in the 2nd epoch, to a stable 0.100 in the 59th epoch as in the Figure 4.

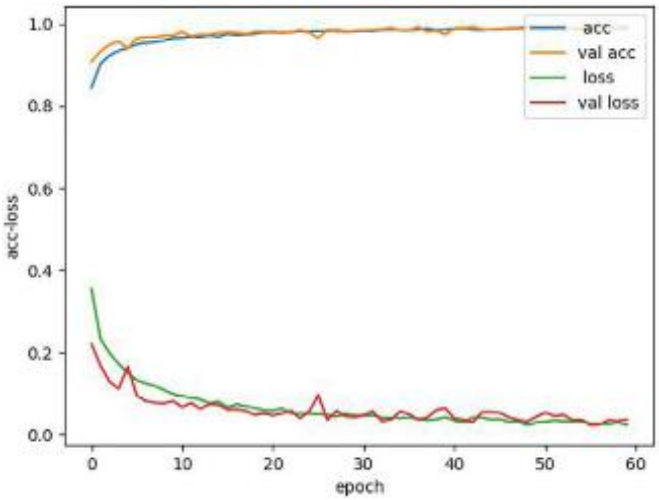


Figure 4. Model Train-and-Validation Accuracy-and-Loss

Table 2. Ablation Studies with benchmark model comparison

Classes	Precision	Recall	F1
Atelectasis	0.973	0.988	0.992
Cardiomegaly	0.974	0.986	0.989
Effusion	0.982	0.987	0.992
Infiltration	0.976	0.973	0.985
Mass	0.936	0.979	0.991
Nodule	0.988	0.998	0.988
Pneumonia	0.994	0.996	0.994
Pneumothorax	0.993	0.989	0.989
Normal	0.992	0.989	0.989

The rapid rise in accuracy, and the steady decline in loss – agrees that model efficiently captured important features and minimizes errors. Our high accuracy affirms this that model generalized well on test dataset. In addition – its smooth, monotonic decrease in loss without a sudden burst. It implies the model learns well even with the instability of the vanishing gradients, to accurately handle class identification and recognition.

3.2. Benchmark Comparison

To validate the performance of the proposed Xception model, we tested several other transfer learning models to include MobileNetV2, DenseNET, EfficientNetV2, RESNet, VGG16, and Stacked model with XGBoost meta-regressor – to yield a comparison of the results as presented in Table 3 ablation studies expressed as in Figure 5. The proposed model accurately identifies and classifies the lung cancer, efficiently reducing noise inherent the adopted dataset [73]. Proposed model yields an Accuracy 1.000, precision 0.994, recall 0.989, and F1 0.989 – to accurately classify all 35,589-images with no misclassified instances as in Table 3 [74]. Our model successfully recognizes and accurately classified the rice leaf disease. The proposed model shows excellent reliability in classifying correctly and consistently. These are also consistent with high validation accuracy and low loss, indicating that the model fits well with the training data, and generalizes well to unseen (test) data [75].

Table 3. Ablation Studies with benchmark model comparison

Features	MobileNET Ref [76]	EfficientNET Ref [28]	VGG16 Ref [77]	Stacked Ref [22]	DenseNET Ref [78]	RESNet Ref [79]	Proposed Xception
Accuracy	0.973	0.919	0.852	0.992	0.969	0.939	1.000
Precision	0.974	0.959	0.896	0.989	0.976	0.919	0.994
Recall	0.982	0.948	0.822	0.992	0.947	0.981	0.989
F1	0.976	0.973	0.863	0.985	0.974	0.989	0.989

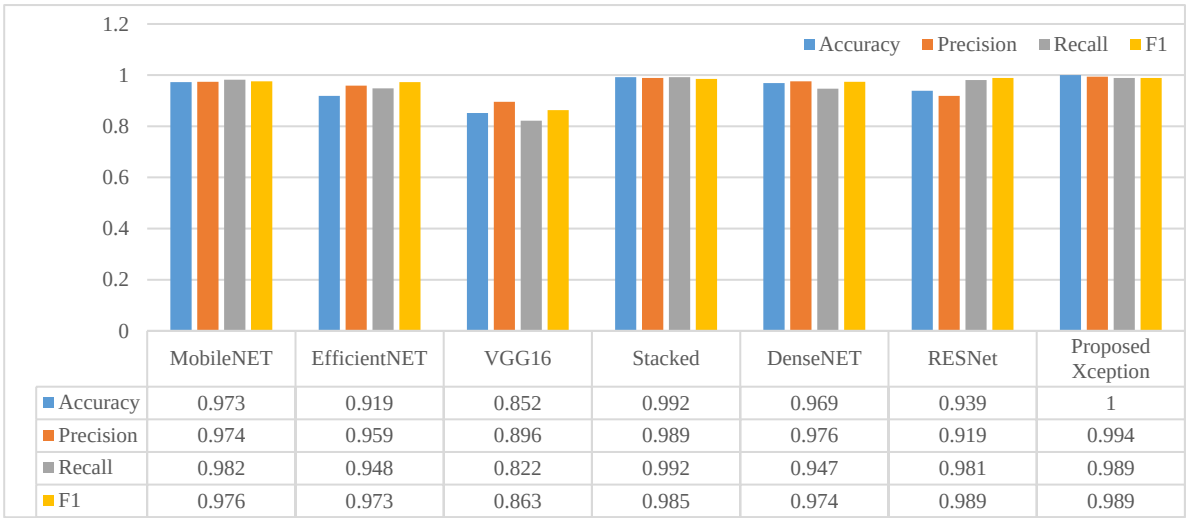


Figure 5. Ablation report for the Proposed versus benchmark model

4. Conclusion

A resultant balance between specificity and recall is crucial as emphasis on one often ripples inconsistency across the dataset, and yields a significant tradeoff. And while Accuracy provides the requisite insight into the explored dataset complexities that may result in perceived distorted values – F1 assess the reliability of model Accuracy and performance on imbalanced dataset features as the altruist model's effectiveness in classifying positive cases without overprediction of false positives. The chest X-ray image is a reliable method for early lung disease prediction. Our model exploit image enhancement over a region of interest (ROI) estimation to result in disease identification via publicly available X-ray datasets. We extracted visual, shape, texture, and intensity from each ROI followed by normalization via the AMF-CLAHE-and-VMD robust technique to enhance image classification results – with our Xception model yielding lung cancer image detection with an Accuracy of 1.000.

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