**Primary Tumor and Lung Cancer Prediction on Dual Energy CT Images for Nodal Metastasis using Deep Learning Technique**

**Abstract:** The detection of Lymph Node Metastasis (LNM) is one of the greatest clinically essential tasks in terms of the existence and recurrence of lung cancer. It is still challenging to identify medical strategies and pretreatment choices for patients with malignancies based on preoperative identification of nodal metastases. Tumors are identified using quantitative Computed Tomography (CT) features of shape, first-order, second order, and higher-order textures. Statistical and machine learning studies are utilized to integrate clinical data and assess the attributes of their individual. This research discovered several radiomic features associated with distant, nodal, and histological spread, which have great capability as an imaging biomarker for pathological diagnosis and target therapy selection. It developed a novel deep prediction technique with a Size-Related Damper Block (SR-DB) for the identification of Nodal Metastases (N-Mets) from main lung cancer tumors utilizing Gemstone Spectral Imaging (GSI) dual-energy CT. In an implementation, a recommended strategy for N-met prediction trained on the 40 keV dataset offers an accuracy of 0.89 percent and a sensitivity value of 0.95 percent. The results show that tumor heterogeneity and size aid in determining whether nodal metastasis from the initial tumor is absent or present in the proposed model.

**Keywords-** Lung cancer, Nodal metastasis, GSI, Deep learning, Damper block

1. **Introduction**

Lung cancer (LC) is a highly popular kind of cancer for many fatalities globally. It is the second-highest popular disease that affects both men and women equally. It is distributed in two major kinds of as Non-Small Cell Lung Cancer (NSCLC) and Small Cell Lung Cancer (SCLC) (Liao, 2012). NSCLC is the greatest frequent kind of lung cancer, which is identified as adenocarcinoma, larger cell carcinoma, squamous cell carcinoma, and Not Otherwise Specified (NOS) (Yamashita, 2016). Distant Metastasis (DM) and Lymph Node Metastasis (LNM) are contributed to cancer mortality by encouraging disease spread. Tumor staging is important for identifying treatment choices such as surgery, chemotherapy, and prognosis (O'Sullivan, 2017; Zhang, 2022). Medical imaging is frequently utilized to detect tumor distribution and severity to provide important data for diagnosis, staging, and therapeutic decision-making while maintaining acceptable diagnostic accuracy (Ruytenberg, 2018; Tsili, 2021; Zhen, 2019). However, it is challenging the disorganized doctor-to-patient ratio and the limitations of radiological diagnosis to obtain a rapid and accurate diagnosis utilizing medical imaging (Ozturk, 2020; Pace, 2022).

Adenocarcinoma is the most common histological kind of NSCLC. Tumor, Nodes, and Metastases (TNM) data is utilized to annotate both NSCLC and SCLC and decide the optimal treatment option (Kim, 2012). The presence of Nodal Metastasis (N-met) has a significant impact on the clinical stage, and prognosis, and is virtually always identified postoperatively (Monfardini, 2021). These people have a 25% probability of living within five years of disease progression and therapy alternatives (Uus, 2022; Crino, 2010; Han, 2022). Prognostic features of CT images in radiometric investigations have recently indicated metastasis and treatment responses (Coroller, 2017). It assisted evaluate Lymph Node (LN) condition in the affected role with lung cancer, and the clinically negative N-met has missed several concerning aspects in the images (Huynh, 2016; Xia, 2022; Campos, 2022; Wang 2021). Figure 1 shows the lymph node with a metastatic tumor in which the portion in the black line represents the metastatic tumor.

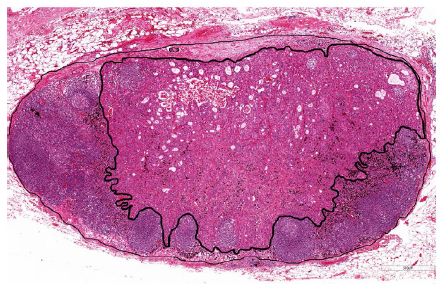


Figure 1 Metastatic tumor in a Lymph node

There are many approaches for obtaining CT power spectrum imaging such as Gemstone Spectral Imaging (GSI) incorporates a rapid Kilovoltage Peak (kVp) changing through dual energy to shift between two separate powers to provide monochromatic images from 40 to 140 kiloelectron volts (keV) (Chen, 2022). The primary goal is to develop a high-performance estimate system for getting a nodal phase on lung CT images by identifying N-met at different energy levels (Schneider, 2021). The Volume of Interest (VOI) of the primary tumor is a vital component of the prediction system. The radiomic features cannot be utilized to identify N-met illness that has been impacted by the tumor, peritumor, and forecasting the primary tumor's nodal stage (Jeon, 2022; Bach, 2012). The present N-met study is comprising some false-positive predictions, and no logical procedure or study to forecast N-met on primary tumors in lung cancer patients (Wu, 2016; Liu, 2021; Heuvelmans, 2021). Figure 2 shows the image of primary lung cancer in a patient.

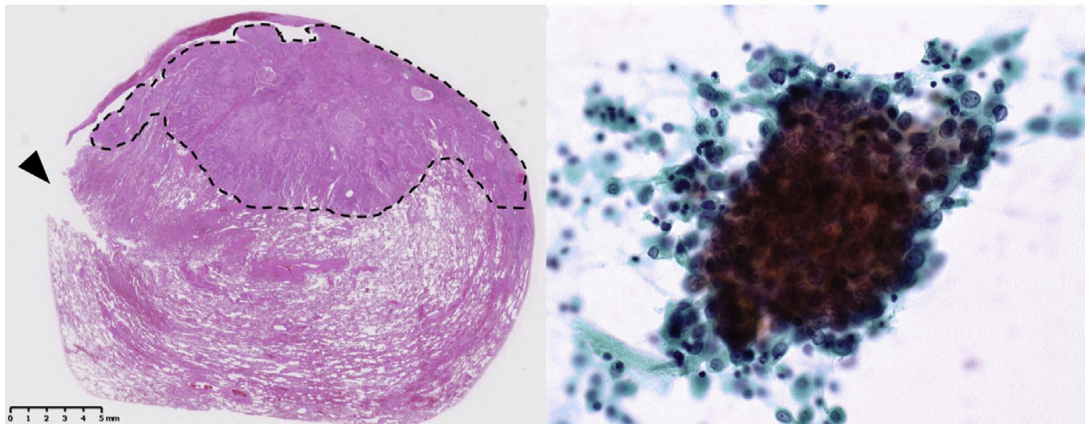


Figure 2 primary lung cancer with positive cytology result

The suggested model would utilize two basic tumor inputs, one with a size-related dilated convolution residual block, and the other with multiple mask convolution representation blocks (Zhu, 2020). It is creating a system that utilizes Deep Learning (DL) to predict VOI objects based on the VOI size and core location of the primary tumor. DL has recently been suggested as a way of defining lung nodules and thereby reducing the number of scans necessary to establish whether it is benign or malignant (Zhang, 2022). Currently, only sensitive tools are available with most research using nodules up to 30 millimeters in diameter. The data from the National Lung Screening Trial (NLST) helped to build a trained lung cancer prediction, which is subsequently utilized to identify benign nodules and rule out further testing (King, 2020; Thomsen, 2012; Gassenmaier, 2020; Wood, 2014; and Park, 2021).

1. **Literature Review**

Several researchers explain their findings and the several related works of many authors as given below:

Muraoka, Yuji, et al. (2022) studied that the AUC for consolidation-to-tumor ratio and maximal standardized application value is 0.733 (95% certainty interval, 0.708-0.758) and 0.842 (95% certainty time, 0.816-0.866), respectively. It is better to use the consolidation-to-tumor ratios from high-resolution CT to determine the sublobar resection which is necessary for patients with medical phase NSCLC rather than the maximum standardized uptake value.

Fu, Yili, et al. (2021) stated that the nomograms are designed and validated for preoperative prognostication of LN metastases in patients along with LC. LC was used to improve a prediction model in a primary cohort of 330 LN locations from affected roles with clinically validated LC. One with LN SUVmax/left atrial SUVmax is shown to be the greatest predictor of LN status, with an Area Under the Curve (AUC) of 0.83 (0.74–0.886) in the initial cohort and 0.85 in the validation cohort.

Yin, Guotao, et al. (2021) stated that a Support Vector Machine (SVM) model is created utilizing seven LN features. The best model had the greatest, lowest, and average accuracy of 91, 66, and 80 percent, respectively, with the lowest, highest, and average accuracy of 62, 54, and 79 percent, respectively, with AUCs of 0.94, 0.66, and 0.81. Metastasis was suspected in LNs with scores ranging from 1.5 to 3.0.

Ismail, Meraj Begum Shaikh, et al. (2021) stated that tumor segmentation and classification are difficult due to the large amount of data in CT scan images and hazy boundaries. The suggested techniques' accuracy, sensitivity, specificity, and classification time are all examined to determine their overall performance. The sensitivity of two-stage neural networks for nodule diagnosis was within radiologists' range at 65 percent, while radiologists' sensitivity varied from 51 to 81.3 percent. The accuracy of classifiers is much greater at 41%, compared to 1-2% for radiologists.

Kriegsmann, Mark, et al. (2020) stated that reliable entity subtyping is crucial for lung cancer treatment stratification. Each patient was randomly assigned to one of three groups training 80 Antibody-Drug Conjugate (ADC), and validation and evaluating 80 SCLC, and 30 skeletal muscles. The results of the image patch and patient-based CNN classification in the test set were 95% and 100%, respectively.

Ferreira-Junior, Jose Raniery, et al. (2020) studied that staging and histology are important in making treatment decisions for lung cancer to use radionics assessment to link measurable difference-improved CT types. The machine learning model predicted the same patterns with an accuracy of 0.92, 0.84, and 0.88 on the receiver operating characteristic curves.

Wang, Xiang, et al. (2019) stated that three hundred people with clinical-stage peripheral lung cancer were examined using five CT scanners. On CT scans, these two VOIs were referred to as the Gross Tumor Volume (GTV) and peritumoral VOIs, respectively. It is initials based on GTV and Planning Target Volume (PTV) features showed an AUC of 0.829 and 0.825 in predicting LN metastasis, respectively. AUC for Radiomic initials was increased to 0.843 and nomograms were 0.869.

Morand, Grégoire B., et al. (2018) studied that the presentation evaluation on entirely patients with OSCC was performed utilizing pre-therapeutic FDG-PET scans available at the University Hospital Zurich between 2007 and 2016. In a multivariable model, a SUVmax9.5 (P=0.028) was the only predictor that could consistently predict the existence of occult metastatic illness in cN0 individuals. A higher SUVmax (9.5) tumor was combined with a better incidence of undetected metastatic nodal illness and an inferior prognosis in the primary tumor.

Hosny, Ahmed, et al. (2018) stated that are looking at how deep learning is utilized in medical imaging to automatically quantify radiographic qualities and assist in better stratifying patients. The CNN can drastically stratify patients into low and high-transience threat units in mutually the radiation and surgery datasets. This discovery is accelerating research into the clinical, molecular foundations of deep learning networks, and confirmation of future information.

Im, Hyung-Jun, et al. (2018) stated that the metabolic and pathological factors are assessed for OLNM. Lymph node metastasis was found in 24 of the patients, or 17.2% of all the patients. Metabolic Tumor Volume (MTV) and Total Lesion Glycolysis (TLG) were 4.61 ± 3.99 (0.5% greater than 17.8%) whereas SUVmax and MTV were 4.18 ± 6.39 (0.34% more than 34.6) and 16.13 ± 28.86 (0.5% greater than 164.2), respectively. SUVmax and density metrics are related to an elevated risk of Occult Lymph Node Metastasis (OLNM) in small peripheral NSCLC. Table 1 demonstrated the comparison of the reviewed literature:

Table 1. Comparison of the reviewed literature

|  |  |  |
| --- | --- | --- |
| **Author’s Name** | **Technique** | **Outcome** |
| Muraoka, Yuji, et al. (2022) | AUC | For medical phase NSCLC patients, high-resolution CT consolidation-to-tumor ratios are superior to maximal standardized uptake values for sub-lobar resection. |
| Fu, Yili, et al. (2021) | PET | It is generated tumor-to-blood nomograms that take into consideration previously reported clinicopathological risk indicators to better predict the probability of LN metastasis in LC patients before surgery. |
| Yin, Guotao, et al. (2021) | SVM | The model is condensed into a scoring system, and clinicians with NSCLC find it easier to stage their patients' cancer. |
| Ismail, Meraj Begum Shaikh, et al. (2021) | DTCWT | The suggested techniques' accuracy, sensitivity, specificity, and classification time are all examined to determine their overall performance. |
| Kriegsmann, Mark, et al. (2020) | CNN | There was using CNN image classification models for tumor differentiation offers both benefits and downsides. |
| Ferreira-Junior, Jose Raniery et al. (2020) | Volumetric segmentation | Wavelet powers, data measurements of association, and the highest possible from a co-existence matrix are among these properties. |
| Wang, Xiang, et al. (2019) | mRMR feature | The suggested nomogram is aid in the preoperative prediction of LN metastases in peripheral lung adenocarcinomas. |
| Hosny, Ahmed, et al. (2018) | CNN | This discovery is accelerating research into the clinical and molecular foundations of deep learning networks, and confirmation of future information. |
| Morand, Grégoire B., et al. (2018) | SUVmax | A higher SUVmax (9.5) tumor was combined with a better incidence of undetected metastatic nodal illness and an inferior prognosis in the primary tumor. |
| Im, Hyung-Jun, et al. (2018) | SUVmax | MTV is provided as a potential signal for sublobar excision in clinically node-negative small-cell NSCLC. |

1. **Background Study**

The correct diagnosis of LNM is strongly associated with persistence and repetition following lung cancer. Preoperative prediction of nodal metastases continues as an experiment in cancer patients when deciding on surgical strategies and pretreatment options. All trial participants get 11 monochromatic images ranging in keV from 40 to 140. It is utilizing a model of a 40 keV dataset, and other energy levels have a substantial difference. The 5-fold cross-validation approach explains why a lower keV is better at predicting N-met in primary tumors. It is also used multi-power stages images as inputs to combine the characteristics of various keV to improve accuracy. It is expected to categorize additional classifications from the initial tumor, such as surgical resection suggestions (Wang, 2022).

1. **Problem Formulation**

According to the World Health Organization, lung cancer is some of the leading effects of mortality in humans. Persons with lung cancer in any of the other organs, such as the bladder, cervix, breast, colon, or prostate, have a five-year survival rate of less than 14 percent, which is much lower than the five-year survival rate for people with lung cancer. Many researchers have also communicated the importance of the extracted feature, which impacts the overall efficiency, where a DL-based lung cancer prediction model is developed. The model considers the lung smoothing improvement in image quality and segmentation as this component of pre-processing that helps the level of off noise in the in-built image. RA Conv is used to layer the learning process and to provide the highest availability of images during real-time testing. The Damper block works to produce a near-identical image to the original image, and a discrimination network is utilized to validate the extraction of the new image.

1. **Research Methodology**

This section contains the techniques, datasets, damper block, and proposed methodology. The detailed description of various techniques that use in the methodology are described below:

* 1. **RA-Conv Layer**

It is using the residual assembly to minimize training parameters and time. It is a hybrid attention technique to enhance the system by concentrating on the extra relevant portions of the feature maps by taking just the key care of the information. It is utilized in RA-Conv that a hybrid attention module is within the residual convolution. The classifiers are appropriately known as Classifiers in RAC and Classifiers out of RAC (Guo, 2022). Figure 3 shows the residual convolution structure with hybrid attention below:

Diagram

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Figure 3. Residual convolution structure with hybrid attention

* 1. **Multi‑Level Dilated Residual Convolutions**

The convolution technique is strong and flexible in dynamic features extracted by moving the kernel around the input image. Convolutions are renowned for being translationally functional, which is little degree of shift in an input image, the output remains similar, and shifted by the same amount. In the U-Net transceiver structure, convolutional layers are utilized to separate new robust high-level semantic characteristics. Convolutional layer output is down-sampled utilizing max-pooling layers before being recovered to the original size utilizing up-sampling or deconvolution (Gudhe, 2021). Figure 4 shows a schematic representation of the MLDR block below:

Diagram

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Figure 4. Diagram of an MLDR block

* 1. **Inception-ResNet Block**

A CNN is established on the Inception design series, but with residual connections. The benefit of the Inception module is the pattern of ResNet design and the Inception layer. It is also called the Inception-ResNet block. Figure 5 shows the design details of the Inception-ResNet below (Gonwirat, 2020).

Diagram, schematic

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Figure 5. Architecture details of the Inception-ResNet

* 1. **CNN-based Multiclass Classification**

Image fusion is initially utilized to better the lesion in low-purpose in full-frame scintigraphy images by combining the anterior- and posterior-view point images of every bone scan to repeatedly identify LC metastases in scintigraphy images. The dataset used in this research is increased using parametric variation-based information growth to maximize the CNN-based network's capacity to categorize images. An end-to-end CNN network is constructed for the categorization of the fused images by first information extraction and aggregating hierarchical features of an image. Figure 6 shows the suggested multiclass classification technique (Guo, 2022).

Chart

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Figure 6. The CNN-based multiclass classification method

* 1. **Dataset**

The proposed model is trained and evaluated by using KeV CT images at different energy levels (KeV) i.e., 40 KeV, 70 KeV, 100 KeV, and 140 KeV. Figure 7 shows the description of primary lung cancer test cases which representing the dataset in detail. The proposed model is compared by 40 KeV dataset to an existing method with SR-DB and ResNet-50. The three parameters are taken as specificity, sensitivity, and accuracy to investigate the efficiency of the proposed model. The values of specificity and sensitivity are calculated on different energy levels and compared with the existing method.

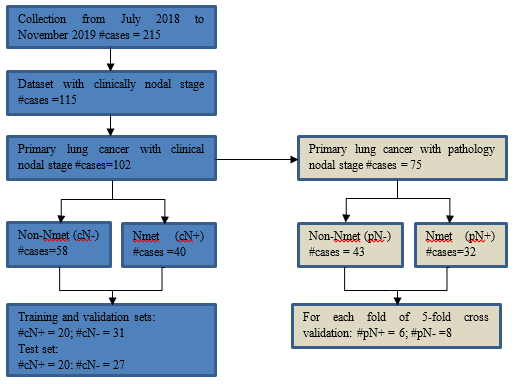


Figure 7 flowchart representing the detail of dataset collection (Wang et al., 2021)

* 1. **Pseudocode**

**Start**

1. Read cancer image dataset as input, where cancer image →C

2. IP (Segmentation, Smoothing, Enhancement); IP = Image-preprocessing

3. Perform IP →C

4. FR (Area, Eccentricity, Energy, Entropy); FR = Feature extraction

5. Do FR → C

6. Enhance metastatic area by→

7. Damper block =;

8. Take RA Conv with as

9. RA Conv with as →InRa

10. RA Conv with as →OutRa

11. Cancer stage classified → machine learning process

**End**

* 1. **Damper Block**

The dimension-associated damper block design is to dampen the productivity of the image interpretation level by utilizing the factors of height, volume, depth, and width. A damper block is utilized to equalize the productivity of the prior level with the volume of the initial VOI. It is utilized a Fully Connected (FC) level in the damper block to change the similar elements as a multi-scale dilated residual. Figure 8 shows the operative of the damper block below:

Diagram

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Figure 8. The operative of the damper block

* 1. **Proposed Methodology**

In this proposed work, cancer images are collected from the 40 KeV dataset and in-depth detail of the methodology is described below and shown in Figure 9.

Diagram

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Figure 9. Proposed Methodology

**Step 1: Cancer Image Dataset**

In the first step, a collection of data is done that is of various cancer images. Data collection is obtaining and analyzing relevant information on crucial factors systematically to answer specific evaluation outcomes. The recommended strategy trained on the 40 keV dataset yields the best model.

**Step 2: Image Pre-processing**

After the data collection procedure, the next step is doing data pre-processing. The dataset has been loaded when the data is available in the database. After the pre-processing of the dataset then categorize all the characteristics that can be used in further processing.

* **Segmentation:** Image segmentation is the method of splitting digital images into several sections, which corresponds to pixels or super pixels in the case of images. Segmentation is used to reduce the complexity of an image's representation or to make it more meaningful and easier to understand.
* **Enhancement:** Enhancements are utilized to enhance comprehension of imagery easier and visual perception. The benefit of the digital image is allowed for changing the image's digital pixel values.
* **Smoothing:** Smoothing is frequently used to remove image noise or to create a less pixelated image. Image smoothing is a key image improvement technology that reduces noise from images.

**Step 3: Feature Extraction**

After the image preprocessing, it is necessary to limit the number of resources available while maintaining access to all critical and relevant information. It converts raw data into mathematical attributes while keeping the data set's picture. Image-based features such as shape, texture, and statistical data have been recovered from a picture using a feature extraction method as parameters of area, eccentricity, energy, and entropy.

**Step 4: Pixel-wise Data Aggregation**

After feature extraction, it is improving the metastatic regions in images has become critical for reliable metastasis detection. A pixel aggregation approach is described to excite the metastatic pixels while squeezing the usual pixels.

**Step 5: RA Conv with Damper Block**

In RA Conv, it is remaining related to decreasing the number of training parameters and training duration. It is developing a hybrid attention technique to enhance the network by concentrating on the most significant locations on the feature maps in evaluating just the critical data. It is utilizing the (inRA-Conv) and (outRA-Conv) to denote a hybrid attention component that is positioned inside the residual complexity.

**Step 6: Cancer Stage Classification based on Learning Process**

The last step is a categorization of cancer stages based on a learning process that is used to identify lung cancer in its initial stages. After image processing of the dataset, the classification of the cancer stage is done based on the learning process.

1. **Implementation and Results**

This section is containing implementation through Python which is done using the proposed methodology:

**Result 1:** It is the Receiver Operating Characteristic (ROC) curves diagram with 4 curves. The blue curve is trained to utilize a 40 keV training set, and evaluated utilizing a 40 keV test set, as shown in Figure 10. The orange curve is the training set at 70 keV, while the blue curve represents the test set at 70 keV. The grey curve represents the training set and test set of 100 keV for evaluation. The training set and test set with the yellow curve were 140 keV. It is the N-met prediction results and AUC value for 40, 70, 100, and 140 keV. The greatest AUC model has been trained using the 40 keV test set, which is the least energy concentration of monochromatic images. This proposed technique has 0.95 sensitivity, and the maximum accuracy is 0.89. Figure 10 shows the sensitivity as compared to 40, 70, 100, and 140 KeV. Table 2 shows the value of specificity and sensitivity of the proposed method at different energy levels.

Table 2 The estimation of the proposed model at various energy sets

|  |  |  |
| --- | --- | --- |
| **Energy (KeV)** | **Specificity (FPR)** | **Sensitivity** |
| 40 | 0.89 | 0.95 |
| 70 | 0.85 | 0.90 |
| 100 | 0.84 | 0.81 |
| 140 | 0.87 | 0.75 |

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generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDQRXhpZgAATU0AKgAAAAgABAE7AAIAAAADSFAAAIdpAAQAAAABAAAISpydAAEAAAAGAAAQwuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCYkAQAAgAAABQAABCskpEAAgAAAAM0NQAAkpIAAgAAAAM0NQAA6hwABwAACAwAAAiMAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Figure 10. Comparison graph

**Result 2:** In this part, the model trained at 40 KeV improves the proposed model. In a 40 keV dataset, compare the proposed model with various curves that evaluate the model with SR-DB and ResNet-50. This proposed technique is best compared to SR-DB and ResNet-50. It has a sensitivity of 0.95 and an accuracy of 0.89. Figure 11 shows the ROC curve of the model with SR-DB and Res Net-50. Table 3 demonstrated the comparison of the proposed model with other earlier-developed models.

Table 3 Comparison of the proposed method with earlier developed models

|  |  |  |  |
| --- | --- | --- | --- |
| **Technique used** | **Sensitivity** | **Specificity (FPR)** | **Accuracy** |
| Res Net-50 | 0.89 | 0.69 | 0.56 |
| With SR-DB | 0.91 | 0.78 | 0.84 |
| Proposed method | 0.95 | 0.83 | 0.89 |

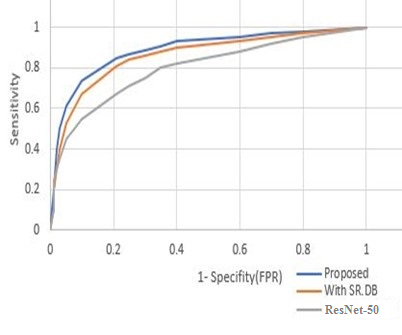


Figure 11. ROC curve of the model with SR-DB and RES Net-50

**Result 3:** These are box diagrams with different predicted risks that highlight the model's expected hazards utilizing SR-DB. In the event of a positive outcome (N-met), it is hoped that the estimated risk is greater in comparison to non-N-met. In the negative-case situation (non-N-met), it expects that the predicted risk is lower in comparison to N-met. Figure 12 shows the predicted risk with SR-DB below:

![Chart, box and whisker chart

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Figure 12.The predicted risk with SR-DB

**Result 4:** These are box diagrams with predicted risk differences that show the model without the dangers of the SR-estimated DB. It is the model's SR-DB-free variant. As a result, demonstrated that the SR-DB model is more successful than other techniques at managing the estimation of N-met. Figure 13 shows the predicted risk without SR-DB below:

![Chart, box and whisker chart

Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RDQRXhpZgAATU0AKgAAAAgABAE7AAIAAAADSFAAAIdpAAQAAAABAAAISpydAAEAAAAGAAAQwuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFkAMAAgAAABQAABCYkAQAAgAAABQAABCskpEAAgAAAAM1MgAAkpIAAgAAAAM1MgAA6hwABwAACAwAAAiMAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Figure 13. The predicted risk without SR-DB

This section of the paper contains the comparative analysis in which various energy levels are applied for lung cancer detection using the DL technique. These are used at several energy levels such as 40 keV, 70 keV, 100 keV, and 140 keV. The proposed technique has the highest 0.89% accuracy. Table 4 shows the comparison based on accuracy and Figure 14 shows the comparison graph below:

Table 4. Comparative Analysis

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Energy Level (keV)** | **Wang et al. 2021** | | | **Proposed Model** | | |
| **Accuracy** | **Sensitivity** | **Specificity** | **Accuracy** | **Sensitivity** | **Specificity** |
| 40 | 0.84 | 0.91 | 0.78 | 0.89 | 0.95 | 0.83 |
| 70 | 0.81 | 0.86 | 0.78 | 0.85 | 0.90 | 0.82 |
| 100 | 0.80 | 0.77 | 0.81 | 0.84 | 0.81 | 0.85 |
| 140 | 0.71 | 0.50 | 0.89 | 0.87 | 0.75 | 0.93 |

Figure 14. Comparison graph

1. **Conclusion and Future Scope**

This research used a deep prediction model known as primary-ring blocks residual estimates using SR-DB to predict the presence or absence of N-met on primary lung cancer tumors. In this research, an RA-Conv with a hybrid attention mechanism is created to autonomously detect lung cancer metastasis using Single Photon Emission Computed Tomography (SPECT) scintigraphy. These have developed an RA-Conv layer with the hybrid attention mechanism in this work. An RA-Conv-based classification network has been suggested for automated feature extraction from images, feature accumulation, and high-level feature categorization. Clinical whole-body scintigraphy images are employed to assess the network that has been built. The results suggest that the method is utilized to assess whether an image covers lung cancer-affected skeletal metastases and to differentiate between lung cancer subtypes. The size information is often used in N-met research to predict LN involvement, which is adding a damper block based on it.

The VOI size already resizing is applied as a proxy for tumor size, while the core block represented the tumor's core, and the ring block represented the tumor's peritumor. It experimented with various datasets of energy levels to see whether it could predict the N-met of different primary tumors to show the model's resilience at lower energy levels. The conclusions demonstrated that the model trained on the 40 keV dataset could better predict the main tumor's N-met. Patients with no visible lymph nodes benefit from the suggested preoperative treatment approach for N-met from lung cancer indicated by the deep learning model. It is wanting to increase performance by including the primary tumor's location by utilizing multi-energy level pictures as inputs to combine the characteristics of multiple keV energies. In the future, it would want to include the main tumor's location to improve performance. It is also utilized multi-energy levels images as inputs to blend the characteristics of various keV to improve accuracy and anticipate to classifications additional classifications as of the main tumors.