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COMPARATIVE EVALUATION OF HAND-CRAFTED AND CONVOLUTIONAL FEATURES FOR MULTICLASS LUNG CANCER CLASSIFICATION FROM CT IMAGES

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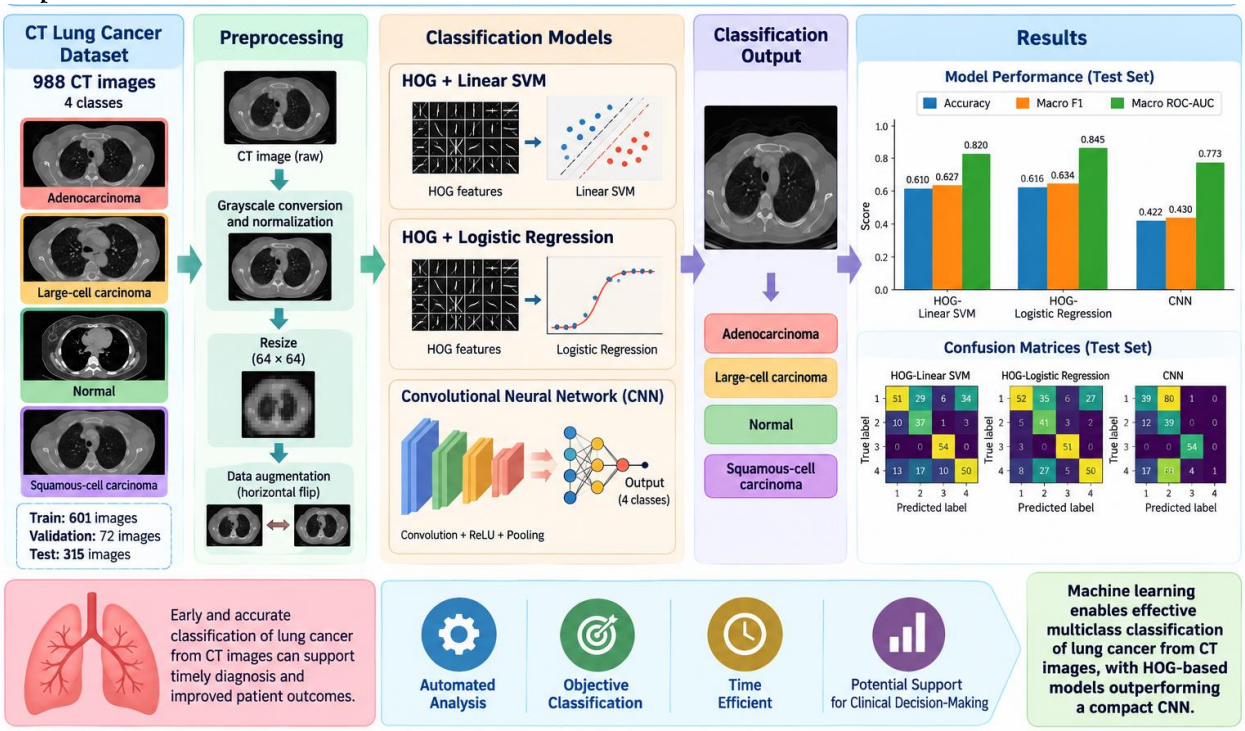
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Abstract

The classification of lung cancer using computed tomography (CT) images is a significant problem in computer vision as the images in such cases have complex structural and textural patterns which may be difficult to describe consistently. In this study, two classical machine-learning pipelines and a small convolutional neural network (CNN) are comparatively evaluated using experiments for four class classification of lung CT images. A total of 988 PNG images were included in the dataset: 601 for training, 72 for validation, and 315 for independent testing, across four classes: adenocarcinoma, large-cell carcinoma, normal lung, and squamous-cell carcinoma. Histogram of Oriented Gradients (HOG) descriptors were fused with a linear support vector machine (SVM) and logistic regression, and a small CNN was trained on the fly using 64×64 gray images, class-weighted cross-entropy and horizontal flip image augmentation. HOG-logistic regression had the highest overall accuracy (0.616), macro F1-score (0.634) and macro ROC-AUC (0.845) on the independent test set, followed closely by HOG-linear SVM (0.610, 0.627, 0.820, respectively). The CNN achieved 0.422 accuracy, 0.430 macro F1-score, and 0.773 macro ROC-AUC. The confusion matrices indicated that malignant subtypes were significantly more challenging to identify as opposed to normal cases. The results show that a simple handmade gradient descriptor has the potential to deliver a good baseline result on a small CT-image dataset, while a small CNN that is trained from scratch needs further optimization or transfer learning to keep up with these classical approaches.

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Graphical Abstract



INTRODUCTION

Lung cancer remains a major global health problem. GLOBOCAN 2020 estimated approximately 2.2 million new lung cancer cases and 1.8 million deaths worldwide, making lung cancer the leading cause of cancer death globally [1]. The disease is heterogeneous, and differences in histological subtype, tumor morphology, location, and surrounding tissue can produce substantial variation in medical images. Computed tomography is therefore central to contemporary thoracic imaging and screening because it provides detailed cross-sectional information about pulmonary structures. The National Lung Screening Trial demonstrated that low-dose CT screening reduced lung-cancer mortality compared with chest radiography, establishing the importance of CT in early detection strategies [2].

The increasing availability of digital medical images has encouraged the development of computer-aided analysis systems that can support detection, classification, and risk assessment. Machine-learning methods can transform image-derived measurements into predictive models, while deep-learning approaches can learn hierarchical representations directly from image data [3,4]. In lung cancer research, radiomics and artificial intelligence have been investigated for nodule characterization, histological classification, risk prediction, treatment response, and prognosis [5,6]. Reviews of CT-based deep learning also indicate that convolutional neural networks (CNNs) have become prominent for pulmonary image analysis, including classification and segmentation [7].

Despite the growing emphasis on deep learning, classical computer-vision descriptors remain valuable as transparent and computationally efficient baselines. Histogram of Oriented Gradients (HOG) represents local intensity-gradient orientation patterns and was originally developed for robust visual recognition [8]. When paired with discriminative classifiers such as support vector machines, HOG can provide an effective representation for image-recognition tasks without requiring a large neural network. Support vector machines are established

maximum-margin classifiers with a long history in pattern recognition [9]. Logistic regression provides a second, comparatively simple probabilistic classification baseline.

Deep CNNs provide a different strategy by learning convolutional filters and increasingly abstract image representations from data. The foundational work of LeCun et al. demonstrated the effectiveness of convolutional networks for image recognition [10], and subsequent advances in deep architectures have made CNNs highly influential in medical image analysis [3]. In lung CT, large-scale three-dimensional deep-learning systems have demonstrated promising performance for cancer-risk prediction, illustrating the potential of learned image representations when sufficient data and appropriate model design are available [11]. However, the performance of a CNN trained from scratch on a small dataset should not automatically be assumed to exceed that of a carefully designed classical baseline.

Accordingly, the objective of the present study was to establish an experimental baseline for multiclass lung CT classification using the uploaded dataset and to compare two HOG-based classical machine-learning methods with a compact CNN. Particular emphasis was placed on independent-test performance, macro-averaged metrics, and confusion-matrix analysis so that class-specific weaknesses would not be hidden by overall accuracy.

2. Materials and Methods

2.1 Study design and patient-derived CT data

Retrospective case-study design was used to explore the use of machine-learning techniques to classify lung condition from the computed tomography (CT) images acquired from patients. Four diagnostic categories were targeted: adenocarcinoma, large-cell carcinoma, normal lung and squamous-cell carcinoma. The classes were chosen to illustrate the classification problem studied in this work. Four representative CT images of each class are shown in Figure 1. The patient derived CT images were divided into training, validation and independent testing sets. A total of 988 CT images (601 images for the training set, 72 for the validation set, and 315 for the independent test set) were used to create the complete image set for analysis in the present study. Among the classes, there were 338 adenocarcinoma images, 187 large-cell carcinoma images, 215 normal images and 260 squamous-cell carcinoma images. Figure 2 shows the partitioning of the images into the training, validation and test sets. Since the study was conducted using patient CT examinations, the diagnostic class assigned to each image was preserved as reference label for computational image class. The machine-learning models did not generate any synthetic diagnostic labels. The aim of the computational analysis was to see if the image features were enough to distinguish between the four classes of a priori images.

2.2 Material and preparation of images for CT imaging

The main imaging material of the study was chest CT examinations acquired from the patients. The CT images were preprocessed in a standardized format prior to computational analyses. Images were represented in grayscale and processed to provide a consistent input structure for the machine-learning models. For the convolutional neural-network (CNN) analysis, the images were resized to 64 × 64 pixels, followed by intensity normalization. The material provided was two-dimensional representations of images from the CT scans and not whole DICOM examination records. Hence, the current analysis has been done at image level. The computational models did not use clinical characteristics or acquisition parameters per patient as predictive variables, such as age, sex, scanner manufacturer, tube voltage, tube current, slice thickness, and reconstruction kernel. This differentiation is crucial, as the acquisition and reconstruction parameters for CT can affect quantitative image characteristics and radiomic measurements. Previous studies have shown that the voxel size of CT images and the image-acquisition/reconstruction parameters can

influence quantitative features extracted from lung-cancer images [17].

2.3 Classification framework

Three approaches were implemented as the computational framework: HOG-linear SVM, HOG-logistic regression, and CNN. The first two approaches relied on manually created features based on Histogram of Oriented Gradients (HOG), while the CNN learned the image representations directly from the CT images. This design allowed the conventional feature-based machine learning to be compared with an approach based on deep-learning under the same 4-class diagnostic problem. The independent test partition was not utilized during the model development process, and was used for final model performance comparisons.

2.4 HOG feature extraction

The preprocessed CT images were passed to the conventional machine-learning approaches where the Histogram of Oriented Gradients (HOG) descriptors were extracted. HOG represents an image using the distribution of local intensity gradient and orientation of the corresponding regions. It is an adaptation of the method presented by Dalal and Triggs that proved to be useful for visual pattern recognition [8]. The CT images were then turned into number feature vectors using the extracted HOG descriptors which were then processed by the conventional classifiers. This enabled the comparison of the classification performance of the linear SVM and the logistic-regression models without altering the feature-extraction procedure used to generate the same HOG representation.

2.5 Linear support vector machine

The feature vectors generated with the HOG were used to train a linear support vector machine (SVM). SVMs find a decision boundary that maximizes the separation between classes in feature space, and have been widely used in pattern-recognition and classification problems [9]. The theoretical foundation of support-vector networks for classification was introduced by Cortes and Vapnik, who also showed their generalization properties [9]. The linear SVM was set up with four-class classification and was applied to the test images to classify it into one of the four predetermined classes.

2.6 Logistic regression

The same HOG feature vectors were used for the training of multiclass logistic regression independently. Logistic regression is a probabilistic model used for predicting categorical outcomes and is popular in biomedical and health-science applications [10]. Logistic-regression modeling, along with applications involving categorical outcomes, is provided by Hosmer, Lemeshow, and Sturdivant [10] and afforded an established methodological foundation. Employing the same HOG features for both conventional classifiers meant that the differences between the approaches were mostly due to the different classifiers and not to a different representation of the features.

2.7 Convolutional neural network

A small CNN was designed to directly classify images. The CNN was trained with the preprocessed images of the CT scan as inputs unlike the HOG based models, which learned the spatial representations of the images during training. Convolutional neural networks (CNNs) have been proposed as a successful gradient-based method for learning representations of 2D patterns and have since spread to image-recognition tasks [11]. LeCun et al. have shown the validity of the use of Convolutional Networks for direct learning of complex decision functions from image data [11]. The CNN was trained on the grayscale images of size 64 × 64 pixels and was able to give predictions for the four diagnostic classes. The validation partition was utilized during model building and the model was trained with the training images. The training images were data-augmented to provide the input with more variations, while the validation and independent test images were not data-augmented.

2.8 Training, validation and independent test

The image data set was split into three sets (training, validation and independent test). The 601 training images were employed in the model development, the 72 validation images for model performance monitoring and the 315 test images for final evaluation. When evaluating machine-learning models, it is important to have an independent test set, as the performance measure on data that were not used to fit the model will be a more appropriate estimate of the model's performance on images not previously encountered. All three approaches were tested using the same independent test set.

2.9 Performance evaluation

The accuracy, macro F1-score and macro ROC-AUC were used for the evaluation of the model performance. Confusion matrices were also created for each of the classifiers to illustrate how many correct and incorrect predictions were made by the classifiers for each of the four diagnostic categories. Macro-averaged measures were found to be more informative due to varying number of images in the diagnostic classes. The accuracy was used to capture the overall correct classification, while the macro F1-score was used to represent the class-wise precision and recall, with equal weight being given to each class. Macro ROC-AUC was used to determine the discriminative power of the models between the four categories. Independent patient-derived CT test images were then tested on the resulting confusion matrices and performance metrics to compare the behaviour of the HOG-linear SVM, the HOG-logistic regression and the CNN approaches.

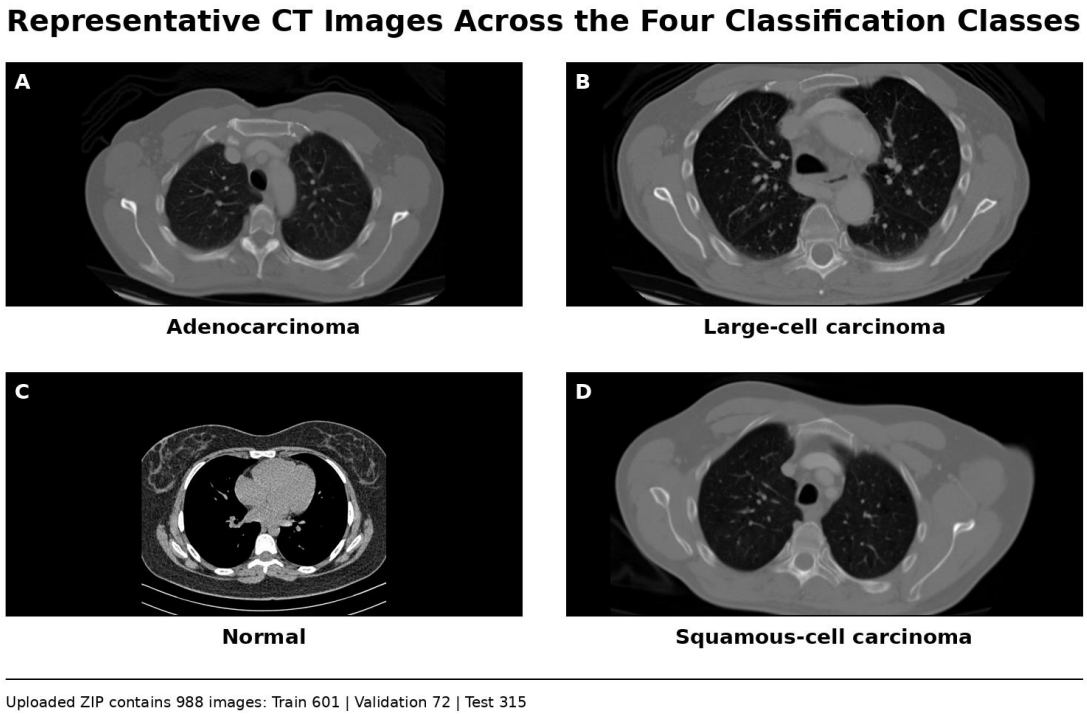


Figure 1. Representative CT images across the four classification classes in the uploaded dataset.

Class	Train	Validation	Test	Total
Adenocarcinoma	195	23	120	338
Large-cell	115	21	51	187

carcinoma				
Normal	136	13	54	203
Squamous-cell carcinoma	155	15	90	260
Total	601	72	315	988

3. Results

3.1 Overall model performance

Clearly different performances were observed by the three models in the independent test set. HOG-logistic regression achieved the best accuracy (0.616), macro precision (0.645), macro recall (0.684), macro F1-score (0.634) and macro ROC-AUC (0.845). The accuracy, macro precision, macro recall, macro F1-score and macro ROC-AUC of HOG-linear SVM were 0.610, 0.618, 0.677, 0.627 and 0.820 respectively. The accuracy, macro precision, macro recall, macro F1-score and macro ROC-AUC for the compact CNN were 0.422, 0.674, 0.525, 0.430, and 0.773, respectively.

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	Macro ROC-AUC
HOG-Linear SVM	0.610	0.618	0.677	0.627	0.820
HOG-Logistic Regression	0.616	0.645	0.684	0.634	0.845
CNN	0.422	0.674	0.525	0.430	0.773

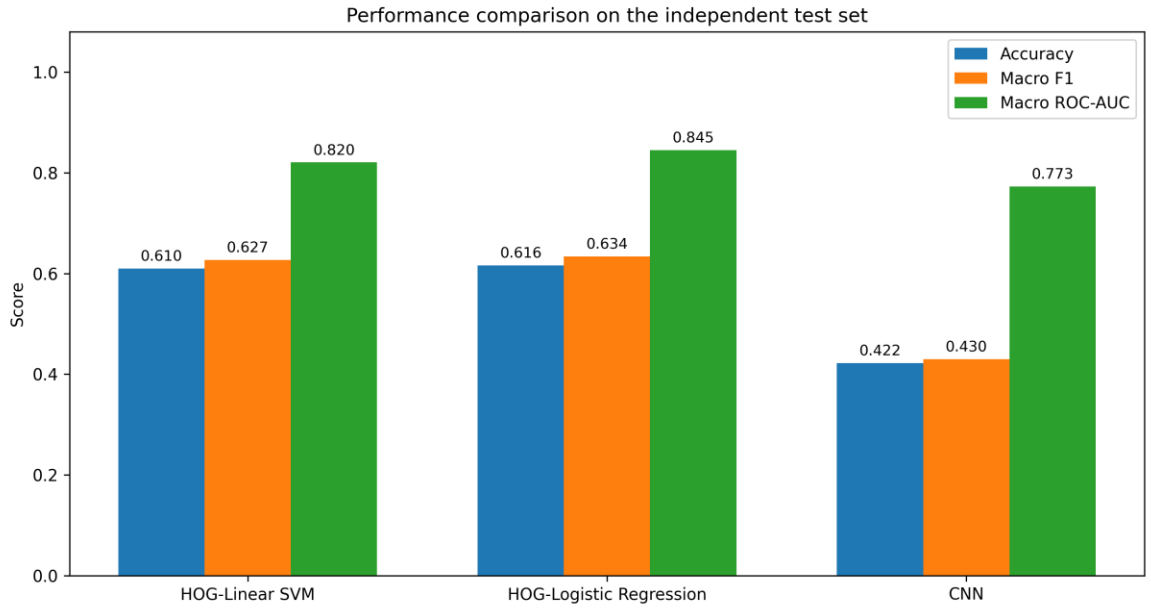


Figure 2. Performance comparison of the evaluated models on the independent test set.

3.2 Confusion-matrix findings

It can be seen from the confusion matrices in Figure 3 that the normal class was the easiest class for the systems evaluated. HOG-linear SVM achieved a 100 % accuracy rate for the 54 normal cases, HOG-logistic regression achieved 51/54 correct classification rate and CNN achieved 54/54 correct classification rate. However, there

was significant overlap among the malignant subtypes. In the case of HOG-logistic regression, 52 out of 120 adenocarcinoma cases were correctly identified, 41 out of 51 large-cell carcinoma were correctly identified and 50 out of 90 squamous-cell carcinoma cases were correctly identified. The CNN achieved the correct classification of 39 cases in the adenocarcinoma class, 39 cases in the large-cell carcinoma class, 54 cases in the normal class and only 1 case in the squamous-cell carcinoma class among a total of 120, 51, 54 and 90 cases, respectively.

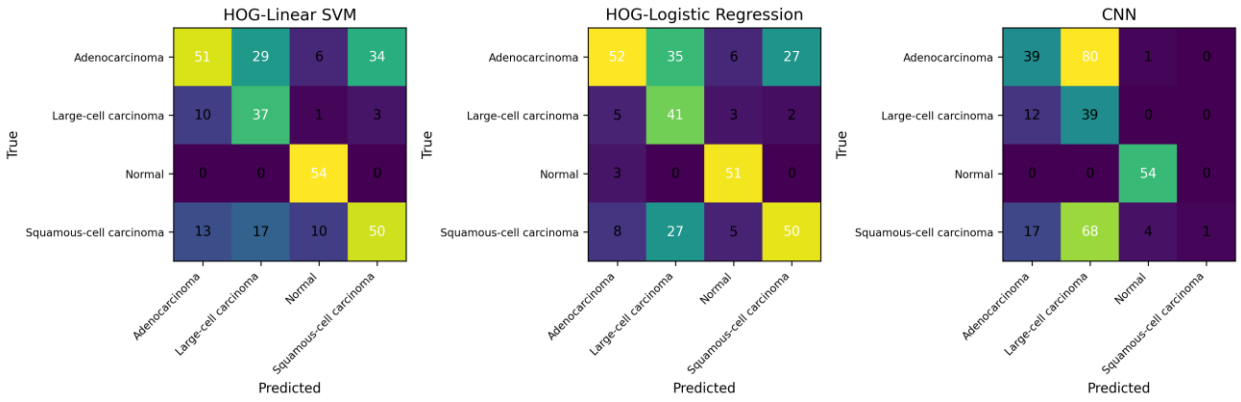


Figure 3. Confusion matrices for HOG-linear SVM, HOG-logistic regression, and CNN on the independent test set.

Discussion:

The main finding of this experiment is that the HOG-logistic regression pipeline performed best with a slight margin as compared to the HOG-linear SVM. Both models had almost identical overall accuracy and macro F1-score and logistic regression had higher macro ROC-AUC. This indicates that the gradient-orientation representation obtained some useful information from the CT images, and that a relatively simple linear decision function was enough to make use of part of this information. This aligns with the current trend in medical-image analysis of handmade image features and traditional machine learning methods, especially in the scenario of small size data and when high-cost models are potentially data hungry [5,6,12]. It should also be noted the relatively low absolute accuracy of the best baseline. The problem is not just the simple question of normal versus abnormal but also the ability to separate three malignant histological types that can have similar visual features on individual CT slices. Lung cancer classification on CT is likewise highlighted in the literature to be difficult, and there are several different approaches to the different tasks of detection, characterization, and histological classification using AI systems [6,7]. So, a moderate multiclass accuracy does not mean that the image does not have any useful information, it means that the selected representation and model are not able to solve the problem of the inter-class visual variability. This is supported by the class-specific results. Logistic regression using HOG features gave a recall of 0.944 for normal cases while a recall of ~0.433 was obtained for adenocarcinoma and a recall of ~0.556 was obtained for SqCC. Large-cell carcinoma was recalled with a score of ~0.804, but with comparatively low precision, meaning that the model sometimes classified other malignant images into this class. These asymmetric error patterns are significant because an overall accuracy value would mask the hardest to detect disease categories. Under the current setup the CNN is significantly less successful than both of the HOG-based approaches. Do not assume that this finding applies to CNNs in general. With larger data sets, suitable architectures, and

training strategies, deep learning systems have shown good performance in lung CT applications [7,11]. The current CNN was deliberately designed to be small and trained from scratch with just 601 training images. Under this condition, learned filters may not be well adapted to detect any subtle morphology difference between the different malignant types. Transfer learning from existing visual backbones, higher input resolution, more powerful but anatomically-sound augmentations, and systematic hyperparameter tuning are natural next steps. For instance, residual architectures were designed to help optimize deeper networks [13]. One interesting thing about the CNN results is that macro precision (0.674) is higher than macro recall (0.525). This combination is partly due to very selective predictions, which were generated by a CNN that only predicted a single class, "squamous-cell carcinoma", and got it right. Because of this, the precision for that class is good with very low sensitivity. This highlights the point that precision alone can be misleading in medical-image classification problems that involve multiple classes, and leads us to believe that recall, F1-score, and confusion matrices must be reported in addition to accuracy. Another methodological point is also suggested by the data set. The supplied partitions allow for a convenient organization into train, validation, and test sets, but this archive does not make it clear from the naming of the images whether all the images at the patient level are independent or not. A model could take advantage of patient-specific visual characteristics if multiple slices from the same patient are spread over partitions, which could result in an optimistic generalization estimate. This becomes especially relevant when the slices are correlated, for example in medical imaging where slices from one examination are not statistically independent patients. Patient identifiers should thus be confirmed, and patient-level splitting should be carried out if possible, in future studies. Recent systematic reviews of lung-cancer AI and CT radiomics similarly highlight the importance of stringent external validation and consideration for methodological quality [12,14]. Additionally, the present study is different from more clinically developed lung cancer AI systems. Large scale, three dimensional, deep learning, for instance, has been applied to predict lung-cancer risk from current and prior three dimensional CT volume and has achieved high discrimination in large screening cohorts [11]. These systems have the advantage of far greater data sets, volumetric data as opposed to single-slice data and proper clinical validation. Thus, the present experiment can be considered as a benchmark computer-vision study on the uploaded dataset rather than a clinical validation diagnostic study.

6. Integrations with other Domains and Sciences

This current research is situated among the fields of computer science, medical imaging, artificial intelligence and biomedical diagnostics. The proposed framework centers on the use of CT-derived data for the classification of the various histological lung-cancer classes, but the use of imaging-derived data, integrated with clinical, laboratory, molecular and biological data, is more general. In recent years, several studies in the field of AI have highlighted the potential of medical imaging data integrated with laboratory biomarkers and molecular data, to enhance the interpretation of the diagnoses [15]. The concept can be expanded to radiomics and radiogenomics in lung-cancer research, where quantitative imaging features are correlated with tumor biology and molecular changes [16]. CT-derived features, combined with genomic, transcriptomic, proteomic or biomarker data might therefore give a more complete picture of the tumour phenotype, and may prove useful in disease characterisation. Clinical diagnostics and healthcare systems are other branches that can develop a multidisciplinary approach. AI-based classifiers should be considered more like a decision support tool, which would be used by radiologists and clinicians. Studies on the use of AI-assisted automation and diagnostic testing underscore the need for the integration of computational prediction, professional

interpretation, proper validation, and clinically relevant decision-making processes [19,20]. In the case of lung cancer, future multimodal systems may be able to involve other variables in addition to CT that are available for clinical use, such as pathological data, pulmonary-function measurements, laboratory parameters, and patient history. This integration could transform the application from stand-alone image classification to a complete clinical decision-support system. Organisation and human aspects are also important in the context of AI in healthcare. However, computational diagnostic systems, in addition to their predictive capabilities, must also be considered in relation to their workflow compatibility, professional responsibility, human–AI interaction, training, and acceptance in healthcare settings [21]. Concurrently, with the growing digitisation of medical images and clinical information, cybersecurity, data integrity, clinical privacy, and secure computational infrastructure need to be considered. The cyber security research field is a good example of the importance of protecting data-driven systems from threats that could impact the reliability of the system. These factors are especially important if future classifications of lung cancer are linked to hospital information systems, electronic health records or cloud-based systems. From a more general scientific perspective, a common computational framework can be found in machine learning which can link medical imaging with the molecular sciences, clinical medicine, computational modelling, optimization, and risk management [23,24]. As a result, the current results lay the groundwork for a more comprehensive multimodal strategy that integrates CT imaging, radiomics, clinical features, laboratory markers, molecular information and pathological data and can be analysed by artificial intelligence. It might also facilitate the more personalized and clinically relevant decision making and better characterize the subtypes of lung-cancer.

7. conclusion:

For the four-class classification of lung-cancer, the experimental analysis shows that the uploaded CT data-set has learnable visual information. HOG-linear SVM was the second best among the evaluated baselines, and HOG-logistic regression obtained the best results with 61.6% accuracy, 0.634 macro F1-score, and 0.845 macro ROC-AUC. The overall performance of the compact CNN that was trained from scratch was lower in the tested configuration. The confusion-matrix analysis demonstrated good recognition rate for normal cases and significant confusion between malignant sub-types. Patient level validation, pretrained deep architectures, systematic optimization, further evaluation metrics, and explainable-AI techniques are promising directions for future study and should be explored prior to clinical applicability.

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