and the radiologist still has a very important role in visually inspecting the nodule to confirm whether change has occurred. Along with the measurement of size change, the time interval between measurements is also important in determining whether growth is meaningful. It is not simply enough to say that a nodule is growing, but rather the intent is to understand its growth rate, and this depends on time, with shorter time intervals between scans introducing greater uncertainty. There are currently many algorithms that have been developed. Some focus solely on screening such as Lung-RADS, while others are designed primarily for the incidentally detected nodules. Differences between the algorithms focus primarily on the size thresholds used to define a positive result, the time intervals between repeat scans, the choice of management for a positive finding, differences in the management of nodule subtypes (solid, part-solid, nonsolid), and differences between baseline rounds and repeat rounds. These different algorithms will be compared and data will be presented in terms of the influence on the rate of positive results. An additional consideration here is also how we define a positive result. Some algorithms define the positivity based on a size threshold, whereas others consider this based on a growth threshold or a combination of size and growth. When these growth thresholds are used, the rate of positive results dramatically decreases. In addition to the finding of lung nodules there are many other findings that commonly occur on the scans such as micro-nodules, areas of atelectasis, perifissural nodules, waxing and waning nodules, endobronchial nodules, presumed pneumonias, that might be found by the radiologist but there are no specific guidance rules for management. Here again the radiologist is confronted with the challenge of attempting to balance excess workup against obtaining a firm clinical diagnosis. While many of these examples have no authoritative guidelines as to how they should be managed, some practical guidance is presented. **Keywords:** Screening, False Positives, volumetric

ES01.03
Deep Machine Learning for Screening LDCT

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The first computer algorithms to automatically detect pulmonary nodules in CT scans, based on classical machine learning approaches, were developed almost two decades ago. These systems appeared in commercially available computer-aided detection packages. However, a recent study concluded that such older software systems fail to flag a substantial number of cancerous lesions and have a fairly high false positive rate. Recently, algorithms based on deep learning, in particular, convolutional neural networks, have been developed that report high sensitivity with low false positive rates. Similar deep learning algorithms have been successful in classifying nodules as solid, subsolid or part-solid with accuracy comparable to radiologists, and in estimating the probability of malignancy of nodules. The 2017 Kaggle Data Science Bowl combined these tasks into a single challenge where 2000 teams developed methods to predict, on the basis of a single screening CT scan, whether a patient would be diagnosed with lung cancer within one year of the date of the scan. The 10 best performing solutions are now available under an open source license and form the basis of commercial solutions that show, in recent validation studies, a performance comparable to radiologists. Thorough validation studies are now needed to investigate if the good performance of these deep learning systems can be replicated, independent of CT parameters, and how such systems can be implemented in a lung cancer screening setting. Possibilities include the use of AI software as a second reader, as a concurrent reader, or even a stand-alone reader for a fraction of the cases, when widespread implementation of screening will put a too large burden on scarce radiological resources. In this lecture, I will review the currently available computer solutions and discuss their validation and integration into CT lung screening workflows. **Keywords:** artificial intelligence, deep learning, chest ct

ES01.04
Multi-Phasic Screening - Can We Address Competing Causes of Morbidity * Mortality Such as Coronary Artery Disease and COPD

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Lung cancer, chronic obstructive pulmonary disease (COPD) and cardiovascular disease (CVD) are highly prevalent in the Western population (annual incidences in the Netherlands: lung cancer n=12,200, COPD n=53,300, and CVD n=101,700). This results in a high burden on the health care system and associated costs, with annual costs of 10 billion euros in the Netherlands alone. Furthermore, lung cancer, COPD and CAD are responsible for a high burden of morbidity, with disability adjusted live year reduction of 2.9, 3.4 and 5.0, respectively. For these so-called Big-3 diseases, treatment is most often initiated at late stages due to late diagnosis after development of symptoms. Early detection and treatment will cure many patients in time, and delay or stop disease progression. Therefore, prevention and early detection are crucial. Currently, no screening is performed for the Big-3. The impact of low-dose computed tomography (CT) lung cancer screening on lung cancer stage shift and reduction of lung cancer mortality has been demonstrated.(1,2) These results have led to recommendations to implement CT screening in high-risk individuals in the USA. Population-based studies have shown the strong relationship between CT-derived extent of CAD and COPD, and mortality, also in lung cancer screening setting.(3-8) However, there is as yet no evidence from randomized controlled trials regarding benefit of CT screening for COPD or CAD. As the high-risk population for the Big-3 is comparable (namely long-term [ex-]smokers), combining imaging biomarkers will likely improve CT screening efficiency. Technological developments in CT allow the determination of early imaging biomarkers for the Big-3, namely lung nodule volume, coronary artery calcium score and lung density/bronchial wall thickness with low-dose CT (see Figure). Combined evaluation of early signs of the Big-3 diseases has not been extensively explored yet. Major advantages of integrated Big-3 screening can be anticipated due to shared risk factors (in particular long-term smoking) and thus overlapping at-risk population, simultaneous presence of B3 diseases, and the health economic yield compared to a single disease. However, at this moment there is no single CT acquisition that allows for accurate assessment of all Big-3 biomarkers. In particular, calcium scoring based on low-dose chest CT, while providing a good correlation on a population basis, is inaccurate for determining the score on an individual basis.(9) Furthermore, there are several challenges that need to be addressed in the preparation and establishment of a B3 screening program. These include the need for evidence of morbidity/mortality reduction for screening of COPD and CAD. Also, B3 imaging biomarkers, particularly for COPD, need validation and standardization. Another hurdle is the labour-intensive work required to obtain B3 imaging biomarkers. Also, education and training for evaluation of B3 CT screening examinations is lacking. Finally, the cost-efficiency of integral B3 screening has not been established. The presentation includes discussion of the background of interest in Big-3 screening, estimated health economic consequences of Big-3 screening, status of imaging biomarker development for the Big-3 diseases, screening population and CT scan protocol, and impediments to Big-3 screening implementation. **References:** 1. Aberle DR, Adams AM, Berg CD, et al. Reduced lung-cancer mortality with low-dose computed tomographic screening. N Engl J Med 2011;365:395—409. 2. van Klaveren RJ, Oudkerk M, Prokop M, et al. Management of lung nodules detected by volume CT scanning. N Engl J Med 2009;361:2221-9. 3. Oudkerk M, Stillman AE, Halliburton SS, et al; European Society of Cardiac Radiology; North American Society for Cardiovascular Imaging. 2008.