

Unveiling the Power of Swarm Intelligence: A Holistic Performance Comparison for Lung Cancer Classification

Olivier Monga*

Department of Smart Systems, Middle East University, Amman, Jordan

Abstract

Artificial intelligence based prediction models are being developed to address these issues and may have a future role in screening, diagnosis, treatment selection, and decision-making around salvage therapy. Imaging plays an essential role in all components of lung cancer management and has the potential to play a key role in AI applications. Artificial intelligence has demonstrated value in prognostic biomarker discovery in lung cancer diagnosis, treatment, and response assessment, putting it at the forefront of the next phase of personalized medicine. In this review, we will provide a summary of the current literature implementing AI for outcome prediction in lung cancer.

Keywords: Artificial intelligence; Machine learning; Radionics; Quantitative imaging; Lung cancer

Introduction

The information about active levels of a gene is provided by the gene expression. For gene expression, one of the widely used measurement technique is microarray [1-5]. In the cancer diagnosis and cancer classification types, the gene expression values obtained by microarrays can be utilized. In many studies, the microarray datasets are employed for these purposes. For the selection of biomarker gene subsets, various feature selection algorithms are employed. To this microarray dataset, statistic machine learning techniques are implemented with or without feature selection. Biomarker genes are to classify cancer types, with a highest classification accuracy being identified by the biomarker genes [6-8]. For gene selections, the various techniques reported in literature are utilizing multiobjective algorithms, a hybrid binary Imperialist Competition Algorithm, a binary differential evolution algorithm, a simplified swarm optimization using a Social Spider Optimization algorithm, Artificial Bee Colony, Binary PSO, novel rule-based algorithm, and Shuffled Leap Frog Algorithm, and it has been well explored. However, in this paper, other suitable swarm intelligence techniques have been explored and analyzed comprehensively [7-10]. Lung cancer is a disease that causes cells to divide in the lungs uncontrollably.

Lung cancer symptoms include persistent cough, chest pain, shortness of breath, loss of appetite, and feeling weak or tired. Sometimes, Lung cancer may show no symptoms, making the identification of lung cancer in its earliest stages, a non-certain task. Lung cancer can be caused by several factors including cigarette smoking, family history of lung cancer, exposure to second-hand smoke, and exposure to radon gas. Several treatment options can be implemented for lung cancer patients. The options include radiation therapy, surgery, chemotherapy, or a combination of these treatments. Several factors dictate the treatment options for patients including the extent of the cancer, a person's overall health and lung function, as well as certain traits of the cancer itself. In many cases, more than one type of treatment is used [11].

Artificial intelligence

Artificial intelligence software tools with minimal human interaction have been used in genetics, patient demographics, and medical imaging for research and clinical applications. In radiology, AI tools can be used to interpret medical images, determine regions

of interest, and provide clinicians with predictive or diagnostic information about the patient. More recently, deep learning has been used on medical images without the need for handcrafted features [12].

Machine learning

Deep learning is a subset of machine learning based on artificial neural networks that mimics the structure and function of biological neurons, such as those in the brain [13]. In deep learning, the computer can recognize and predict patterns within large data sets without human interaction. Artificial intelligence can play an important role in radiology, with the potential to increase a radiologist's efficiency and improve clinical decision-making [14].

Cancer that begins in the lungs is called primary lung cancer. Cancer that spreads to the lungs from another place in the body is known as secondary lung cancer. This page is about primary lung cancer [15]. Treatment depends on the type of mutation the cancer has, how far its spread and how good your general health. If the condition is diagnosed early and the cancerous cells are confined to a small area, surgery to remove the affected area of lung may be recommended. If surgery is unsuitable due to your general health, radiotherapy to destroy the cancerous cells may be recommended instead. If the cancer has spread too far for surgery or radiotherapy to be effective, chemotherapy is usually used [16].

Radiomics

The extraction of mineable data from medical imaging and has been applied within oncology to improve diagnosis, prognostication, and clinical decision support, with the goal of delivering precision medicine. It involves high throughput extraction of computational features quantifying tissue heterogeneity at the macroscopic level using advanced image processing and computer vision techniques

*Corresponding author: Olivier Monga, Department of Smart Systems, Middle East University, Amman, Jordan, E-mail: Monga777@gmail.com

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[17]. Whereas pathomics provides quantitative information at the micro scale. Radiomic features can be divided into five groups: size and shape based-features, descriptors of the image intensity histogram, and descriptors of the relationships between image voxels

One limitation based radiomics is the high correlation between the features and the input data, as the features are generated from that very data [18]. The radiomics approach has the potential to identify quantitative markers of treatment response earlier in the course of treatment. This can enable treatment to be adapted, intensified or altered earlier in the course of disease in order to improve patient outcomes.

Quantitative imaging

Qualitative imaging is the visual review of imaging by a clinician from which a rendering of disease is present or absent flawed with errors in finding diseases and correctly eliminating disease [19].

Quantitative ultrasound

Quantitative ultrasound Field of ultrasound imaging that aims to quantify the interactions between a compression acoustic wave and a biological tissue for its structural sub-resolution characterization is the Radio frequency.

Conclusion

The focus will lie on the steps which can be supported by the described automatic design methods, because they have already been proven to be beneficial in the building automation domain. Such knowledge management is helpful not only for tool support but also for avoiding misunderstandings in communication between different teams or for exchanging data between them. One such possible assistance is the automatic, evolutionary optimization of the identification procedure with queries to the ontologies.

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