The objective of this work was building a dataset of CT scans from a Latin-American patient cohort with a diagnosis of NSCLC and EGFR mutation, that can be used by the research community to develop prognostic imaging-based algorithms. We propose a non-invasive approach to identify risk of progression based on imaging biomarkers (radiomics) from the pre-treatment CT scan. We report baseline performance metrics and show these surpass predictive models based solely on clinical and demographic data.

INTRODUCTION

- Non-small cell lung cancer (NSCLC) is the leading cause of cancer-related deaths, and epidermal growth factor receptor (EGFR) mutation in patients with NSCLC is present in 15% to 50% of cases.
- Randomized trials have demonstrated that EGFR tyrosine kinase inhibitors (TKI) can promote longer progression-free survival compared with conventional chemotherapy.
- Although osimertinib is currently the standard of care, there is a need for new therapeutic options.
- The automated extraction of quantitative features from CT scans and the use of machine learning algorithms for NSCLC prognosis have been explored by numerous works (Auwärter et al., 2020).
- In this work, we present a radiomics dataset of sixty Latin-American cases treated with EGFR-TKI and categorized into responder and non-responder.
- We report baseline performance metrics that lay ground so that other research groups can work on this issue, as we plan to release the dataset publicly on The Cancer Imaging Archive.

METHODS

- We included NSCLC patients with confirmed EGFR mutation who had clinical follow-up of the disease one year after initiating TKI treatment.
- Patients were classified into two categories based on the progression of their lesion after 12 months of treatment: responsive (stable disease or partial response) and non-respondents (disease progression).
- The main outcome of interest was for the classification of respondents and non-respondents. With a prevalence of 50%, a size of 0.5 and a power of 0.80, a simple size of at least 30 respondents and 31 non-respondents is needed to detect an AUC-ROC of 0.7 or higher.
- A group of experienced radiologists performed manual volumetric segmentation of lesions.
- We extracted radiomics features from the original lesion volume and after applying eleven image filters. The original lesion volumes were processed with eleven different image filters, obtaining over 8400 features per lesion.
- We evaluated multiple radiomics pipelines as combinations of feature selection methods, classification algorithms, and hyperparameter optimization techniques (Figure 1).
- The main outcome of interest was the area under the ROC curve (AUC-ROC) for classification of respondents and non-respondents. Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), accuracy, T1 score, and area under the precision-recall curve (AUCPR) were also measured.
- The selection of the best radiomics pipeline was based on the classification performance evaluated with a stratified 5-fold cross validation approach.
- A logistic regressor was trained with clinical data (gender, age, and smoking status) as a reference of non-radiomics prediction on the performance of 1-year progression. Hyperparameter optimization was performed also with 5-folds cross validation.

RESULTS

- The retrospective search resulted in 114 patients and, after an exclusion criteria (Figure 2), the final dataset consisted of 60 patients: 28 respondents and 32 non-respondents (Table 1).
- The best radiomics pipeline consisted of an ensemble of 12 classification algorithms corresponding to 12 image filters, each trained with 20 input features determined by sequential feature selection (5 random forests, 5 linear discriminant analysis, a support-vector machine, and a logistic regressor).
- The ensemble significantly outperformed the performance of a logistic regression trained with clinical data (p=0.05), with a mean AUC-ROC of 0.82 (±0.01) vs. 0.39 (±0.01) respectively. A comparison of diagnostic metrics for both approaches are shown in Figure 3.
- The radiomics model predicted progression after one year of treatment with a mean sensitivity across folds of 0.71±0.2 and specificity of 0.83 ±0.3.

CONCLUSION

Up to date, there is no publicly available dataset to target this issue. No previous work has addressed this problem in Latin American populations. Our results are presented as a baseline and we plan to release publicly the current dataset to motivate further studies on this topic. These results suggest that radiomics is a promising approach to predict progression in patients treated with TKI therapy.

REFERENCES


Figure 1: Summary of the developing and evaluation pipeline for radiomics models.