Head and Neck Cancer Detection Using Radiomics and Deep Learning

1. ABSTRACT

The present work addresses the challenge of detecting head and neck cancer, a pathology with more than 20,000 estimated cases per year in the USA. The main problem identified is the lack of common understanding between clinicians and data scientists, which hinders research in radiomics and the use of imaging biomarkers for prognosis. The proposal consists of a case study, an architecture and a Deep Learning method designed for the processing and analysis of PET (Positron Emission Tomography) tomographic images. A public radiomics dataset was used for validation. The effectiveness of the method was evaluated using standard quality measures: Accuracy, Precision, Recall, and F1-Score.

As future work, it is proposed to explore a hybrid approach that integrates deductive artificial intelligence supported by the modeling of expert knowledge, as well as the incorporation of modern techniques such as reinforcement learning and assembly methods.

2. PROPOSED METHOD

The proposed architecture for data science consists of three main phases:

1. **Image preparation:** Initial processing of the data.
2. **Image Analysis (Deep Learning):** Use of convolutional neural networks (CNNs) for dimensionality reduction and feature extraction, and recurrent neural networks (RNNs) for serial image learning.
3. **Optimization:** Hyperparameter tuning and evaluation.

Relevant Algorithms and Steps

The algorithms are detailed in phases:

- **Phase 1 - Image preparation:**

1. **Distributed N Frame Selection:** Selection of frames for each series of images of the patient.
2. **Conversion to float:** To avoid data overflow.
3. **Rescaled:** Grayscale adjustment between 0-255.
4. **Conversion to uint8:** Transformation to unsigned integer.
5. **Interpolation:** Resizing to ensure uniform dimensions across all frames.
6. **Data construction:** Creation of the image dataset for analysis.

- **Phase 2 - Image analysis with Deep Learning:**

1. **CNN:** Convolution and pooling layers to extract features and reduce dimensionality.
2. **Time Distributed (TD):** Transformation of the original structure into a sequence of N frames (serial image).
3. **RNN:** Recurrent neural network (GRU or LSTM) that learns from the series of images to classify and predict.

- **Phase 3 - Hyperparameter optimization and evaluation:**

Performance is evaluated by varying key parameters such as N selection (number of frames), build parameters (epochs, batch size, optimizer), layer/kernel density, and Dropout rate.

3. EXPERIMENT DESIGN

The experimental design is divided into the characteristics of the dataset and the configuration parameters of the model.

1) Dataset features

The dataset "18F-FDG PET Radiomics Head and Neck Cancer" was used.

Dataset	Number of samples (Serial PET images)	Dimensions of each frame	Classes
Head and Neck Cancer	124	128x128	Presence or absence of malignant tumor

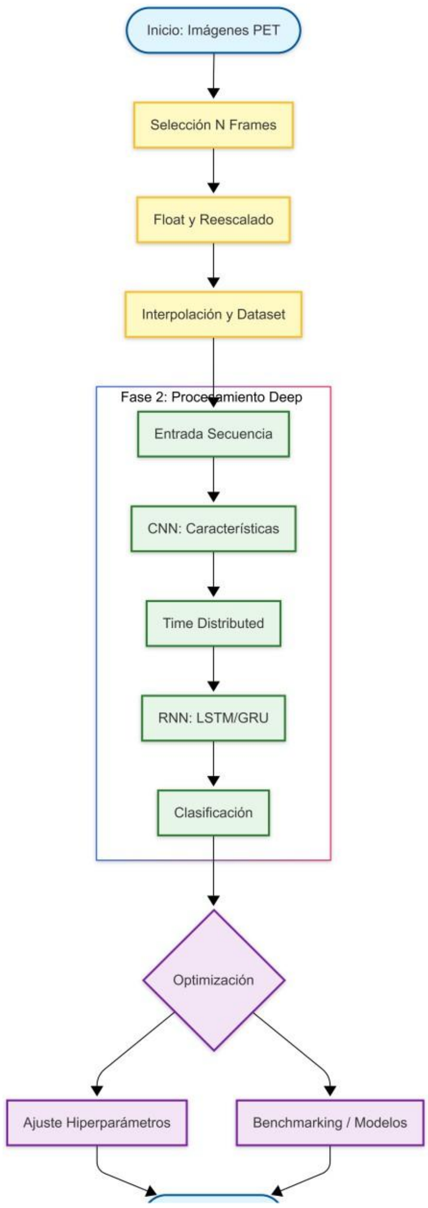
2) Optimization parameters

Various configurations were explored to find the optimal model:

- **Compilation:**
  - Seasons: 10, 20, 30, 40, 50.
  - Batch size: 10, 20, 30, 40.
  - Optimizers: AdaGrad, Adadelta, RMSprop, Adam.
  - Activation functions: Linear, Sigmoid, Tanh, ReLU.
- **Architecture (CNN-TD-RNN):**
  - CNN layers: 1 to 4 levels (filters 16 to 512).
  - RNN: GRU and LSTM with units from 16 to 512.
  - Dropout: 0, 0.1, 0.25, 0.5.
  - Dense layer: 16 to 1024 neurons.

It was also compared with Transfer Learning techniques (MobileNet, VGG16, ResNet50, etc.) and classic algorithms such as Random Forest, SVM and KNN.

4. FLOWCHART



5. RESULTS AND DISCUSSION

Following the proposed method, the following outstanding results were obtained:

1. **Frame Selection (N):** The analysis showed that a number of frames (N) between 10 and 20 optimizes quality measures, reaching values close to 1.0 in Accuracy, Recall, and Precision.

2. **Confusion Matrix:** In tests with N=10 on a set of 25 patients, the model correctly classified 4 cases of absence and 21 of tumor presence, without making errors (0 false positives/negatives).
3. **Comparison of Methods:** The proposed method (CNN-TD-RNN) outperformed other classical architectures and algorithms.

Results Comparison Table:

Method	**Accuracy**	**Accuracy**	**Recall**	**F1-Score**
Proposed Method (CNN-TD-RNN)	**1.0**	**1.0**	**1.0**	**1.0**
VGG16 / ResNet50 / Xception	0.96	0.9545	1.0	0.9767
SVM	0.96	0.9545	1.0	0.9767
MobileNet / KNN	0.72	0.9474	0.75	0.8372

These results indicate that the proposed architecture achieves a perfect classification in the test set, overcoming the generalization of complex pre-trained models.

6. CONCLUSIONS

- Cancer screening is a major challenge that depends on multiple factors, and interdisciplinary collaboration is vital to overcoming obstacles in radiomics research.
- A case study and a Deep Learning method to process PET tomographic images were successfully presented, validated with a public dataset and standard measurements.
- Notebooks were provided to ensure the reproducibility of the experiments.

- Future work is considered articulating with medical institutions for the collection of new images and exploring hybrid AI approaches that combine inductive models with deductive reasoning and expert knowledge.

REFERENCES

- Fuller, Clifton, Hesham Elhalawani, and Abdallah Mohamed. "MICCAI 2018 – Computational Precision Medicine Challenge: 18F-FDG PET Radiomics Risk Stratifiers in Head and Neck Cancer". 29 July 2021. Web. 10 Dec. (2022). DOI: https://doi.org/10.6084/m9.figshare.15075195.v2.