VARIATIONAL AUTOENCODERS FOR LUNG CANCER DIAGNOSIS

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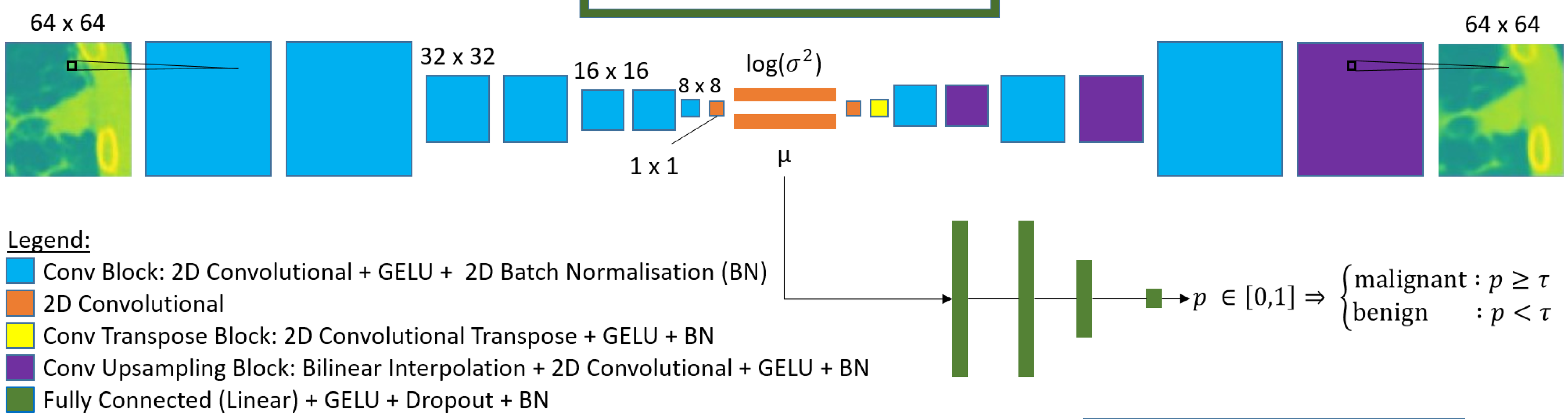
MOTIVATION

Recent advances in generative methods have brought them to the forefront of AI research.VAEs offer many avenues of potential research:

- **EXPLAINABLE FEATURES AND CLASSIFICATION**
- **SYNTHETIC DATA**
- **LATENT TRAVERSALS**

This work aims to demonstrate these methods on a dataset of lung cancer lesions.

VAE MODEL ARCHITECTURE



MATERIALS AND METHODS

DATASET:

Results are produced from the LIDC-IDRI dataset which holds 875 annotated CT scans [2]. Malignancy labels and segmentation masks were agreed by 4 radiologists.

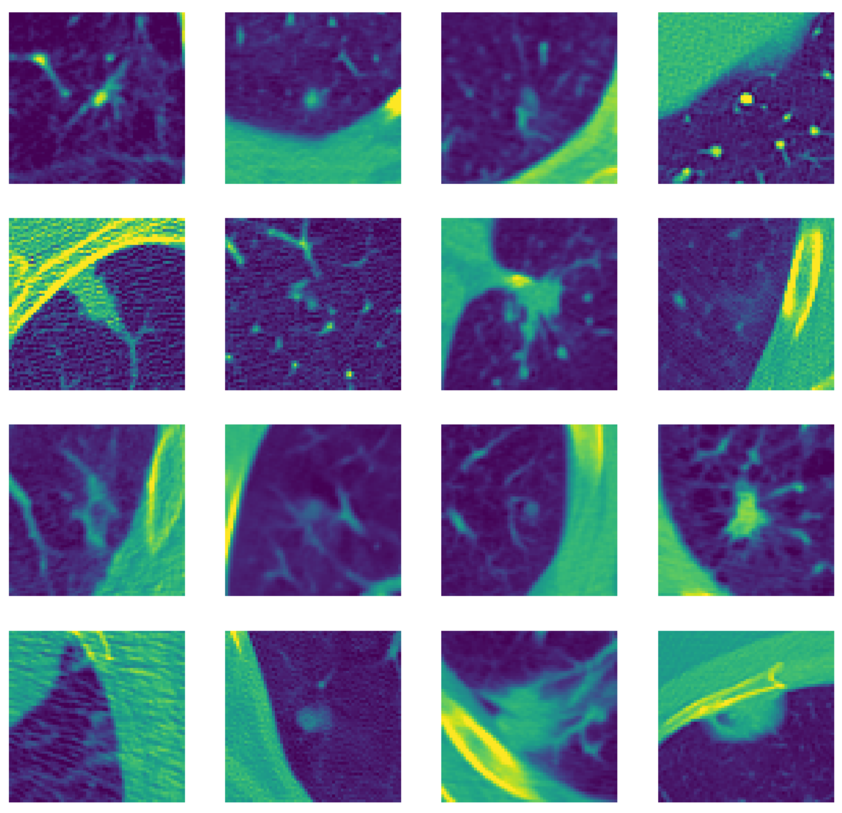
METHODS:

- Gaussian VAE and Dirichlet VAE (encourages disentanglement).
- Extract latent vectors and use as feature representations in Multi-Layered Perceptron (MLP) diagnostic model.
- K-Means and CLASSIX clustering.

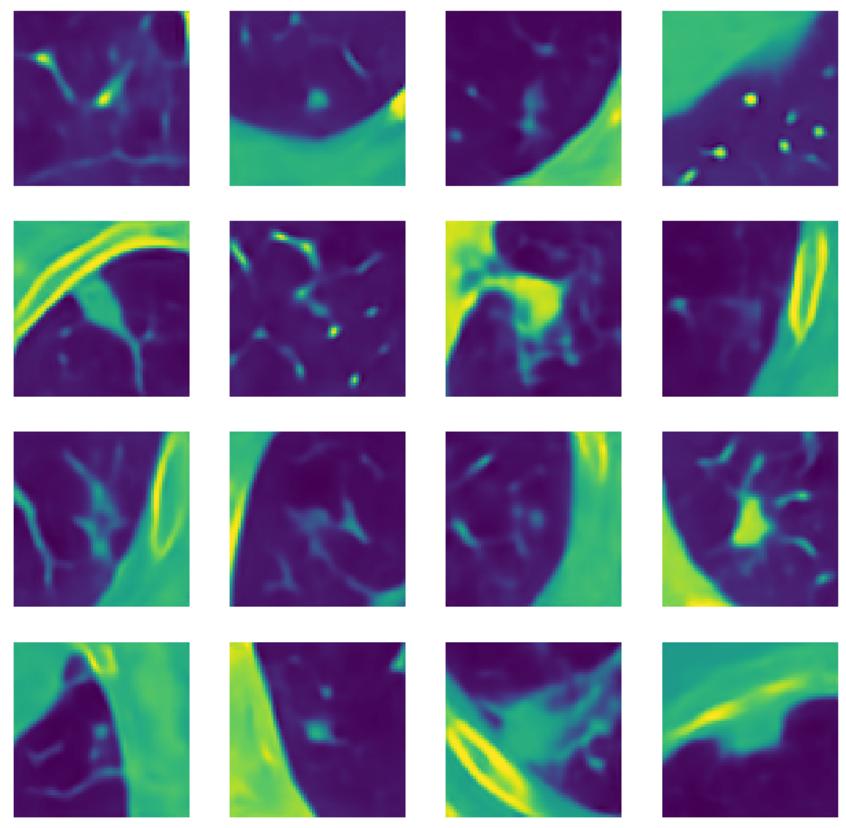
WHY VAEs?

- **unsupervised:** do not require labelled data.
- **generative:** can produce (realistic) synthetic data

ORIGINAL IMAGES



VAE RECONSTRUCTIONS



LATENT EXPLORATION

CLUSTERING:

Shows lesions are separated by shape, patient and class in latent space:

- **58%** of patients had over 50% of slices in a single cluster.
- **70%** of clusters had over 75% of one class (malignant/non-mal).
- See samples from highest proportion malignant/benign clusters.

LATENT TRAVERSALS:.

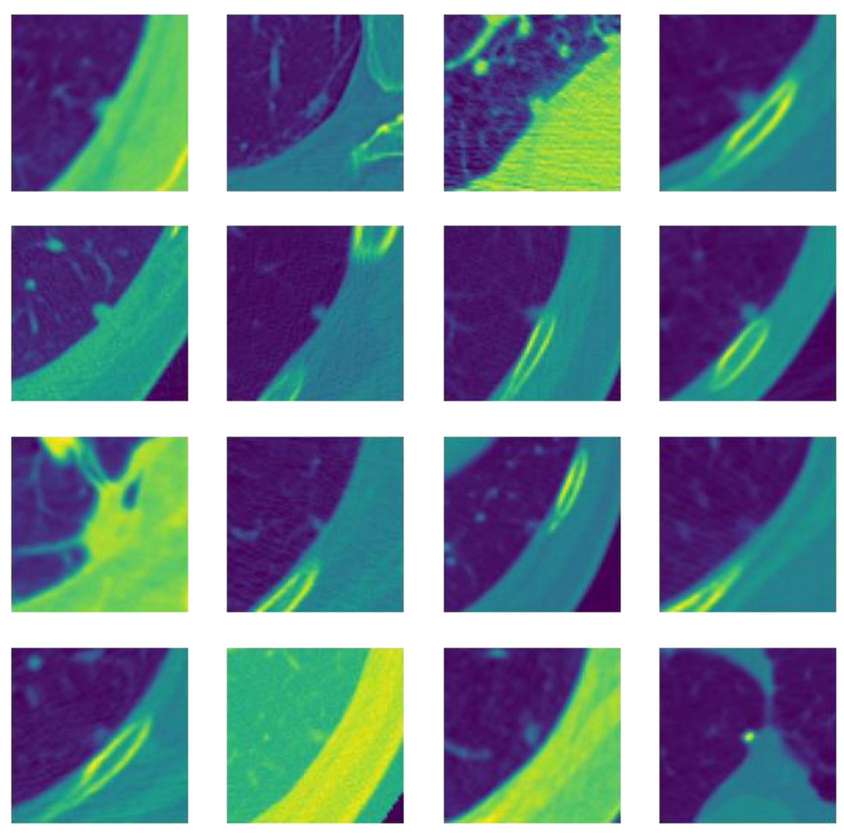
- Initial work shows its possible to find **generalisable and clinically meaningful feature directions.**
- Uses average direction vector between centre of two groups of similar images with/without a given feature. Multiples of the vector are applied to a new image to generate a smooth transition.

LUNG CANCER DIAGNOSIS

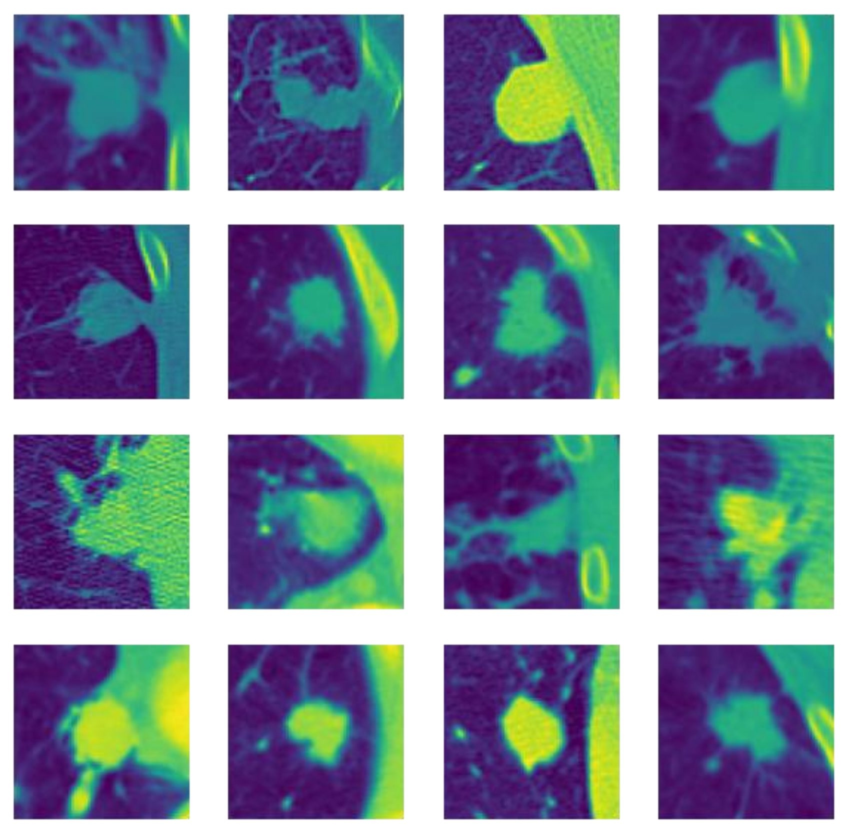
- Results presented show that VAE + MLP combination achieves state-of-the-art performance for lung cancer diagnosis: **0.98 AUC** and **93% Accuracy**.
- Best model uses fine-tuning of encoder with MLP loss to produce classification-optimised latent vectors.
- Direct comparison with Silva et al. [4] who used VAE latent vectors for same task.
- VAE feature vectors are resistant to noise/small changes unlike traditional CNN-derived features.

	VAE_{EM}	VAE	Systematic Review [3]	Silva et al. [4]	Radiologist [1]
AUC	**0.98**	0.89	0.7 - 0.97	0.94	0.85
Accuracy	**0.93**	0.82	0.88 - 0.99	0.90	

BENIGN CLUSTER

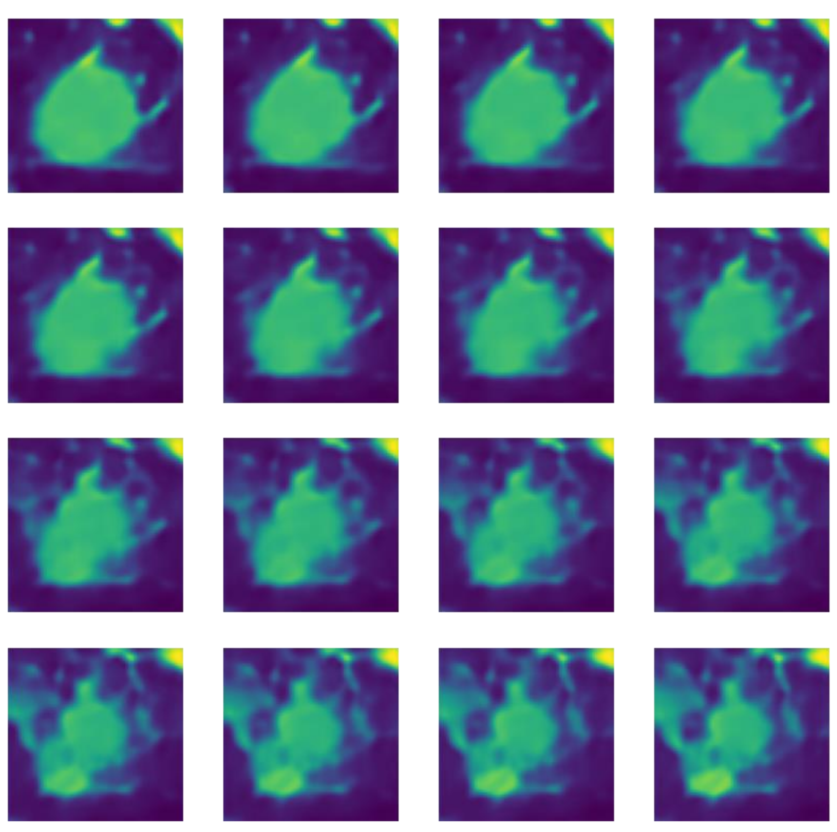


MALIGNANT CLUSTER

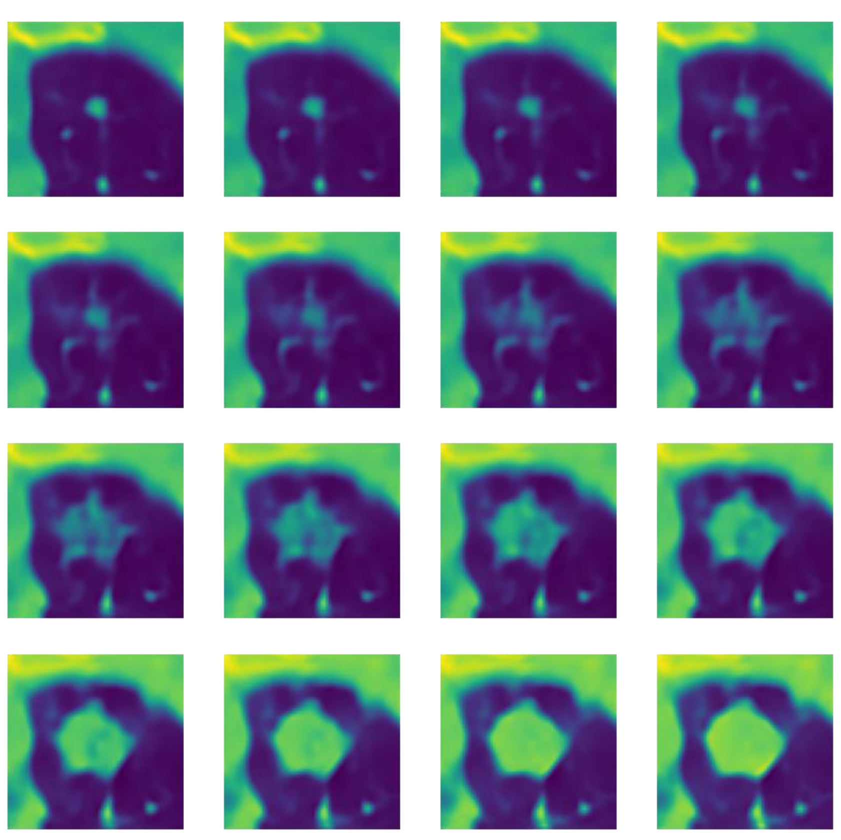


LATENT TRAVERSAL / FEATURE DIRECTIONS

IRREGULAR BORDER



TUMOUR GROWTH



NEXT STEPS

- Use clustering to generate **pseudo-labels** for weakly supervised classification.
- See how latent traversals affect classifications for **diagnostic feature discovery**.
- Create **synthetic data** to help reduce overfitting.
- **Segmenting bone and fat** to remove this impact from the latent space.
- Find direction corresponding to time – **Temporal VAE** for time to event data e.g. pre/post treatment scans. Evolve lesions in time to look for **response to treatment**.

REFERENCES:

[1] Al Mohammad, S. L. Hillis, W. Reed, M. Alakhras, and P. C. Brennan. Radiologist performance in the detection of lung cancer using CT. Clinical Radiology, 74(1):67–75, 2019

[2] Armato, S. G., McLennan, G., Bidaut, L., McNitt-Gray, M. F., Meyer, C. R. et al. [2011]. The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans *Medical Physics* **38**(2) 915–931.

[3] Jassim, M. M. and Jaber, M. M. Systematic review for lung cancer detection and lung nodule classification: Taxonomy, challenges, and recommendation future works. Journal of Intelligent Systems, 31(1):944–964, 2022.

[4] Silva, F., Pereira, T., Frade, J., Mendes, J., Freitas, C. et al. [2020]. Pre-training autoencoder for lung nodule malignancy assessment using CT images. Applied Sciences 10(21).