# Abstract

In this paper, a model is presented for deformable image registration using an approach based on the VoxelMorph algorithm. This model is trained on the MNIST dataset as a lightweight demonstration of the convolutional approach to image registration.

# Introduction

Image registration is an important step in many medical imaging applications. Deformable image registration, where the shape of the image is allowed to be warped to achieve congruence between the initial and target images, is particularly useful in applications such as neuroimaging and organ segmentation, where images may represent cross-sections of volumes that shift in a 3-dimensional space. By mapping a deformation field from one image to another, annotated boundaries in one image can be mapped to their corresponding boundaries in different layers of a scanned volume, allowing for important clinical and research processes such as the 3-dimensional mapping of different organ systems, or the aggregation of multi-modal data into one aligned space.

Previous deterministic algorithms for deformable image registration have been slow and computationally intensive, limiting their practical clinical application. By training a convolutional neural network to approximate the deformation field between pairs of images, this field can be generated significantly faster by the VoxelMorph algorithm than older methods. Efficiency improvements not only provide for more convenient application for the user, but also allow models to be applied practically on much larger datasets, and in use cases where long runtimes present a barrier to deployment.

In this paper, this approach is demonstrated using the MNIST dataset. This dataset, which is made up of grayscale images of handwritten integers from 0 to 9, is both freely available and relatively lightweight, making it ideal for training on consumer-grade hardware.

# Methods

## Dataset

The MNIST dataset is a freely-available set of 70,000 28 x 28 grayscale images of handwritten integers from 0 to 9, with 60,000 original test images and 10,000 test images. The original training split was further divided into 48,000 training and 12,000 validation images. A batch size of 179 was used in the training dataset, where each image in each batch was randomly matched to another image in the training data. Self-matching was allowed in order to allow the model to learn null mappings.

## Algorithm

* Based on VoxelMorph
  + Deformation fields
    - Take a 2-dimensional fixed and target image
    - Define some vector-valued function that maps the fixed image to the target
    - The goal is for this vector field to maintain continuity in the deformation such that, when applied to medical imaging, anatomical structures in the fixed image are preserved in the reconstructed target image.
      * Because this model is trained using the MNIST dataset, interpretability of the mapping is not a focus of this project.
* Loss function
  + MSE reconstruction error
  + Field smoothing error
* Architecture
  + Convolutional neural net
  + 256 filters per layer
* Hyperparameter tuning
  + Trained for 40 epochs
  + Grid search
  + Varied learning rate, tuning parameter in loss function
* Final training
  + Trained for minimum 5/maximum 40 epochs
  + With early stopping if per-epoch validation loss increases

# Results

* Best hyperparameters
* Training vs. validation loss
* Test error on 7
* Test error on 1, 4, 6

# Discussion