Building an AI-Ready Calibrated and Denoised Dataset of Magnetic Anomalies using Citizen Science Contributed *CrowdMag* Measurements

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1. Introduction

Deviations in local magnetic field strengths from what is expected from a regional or global magnetic field model are known as **magnetic anomalies**, whose proper detection can reveal various geophysical features and aid in resource exploration. NOAA's current magnetic anomaly map is known as EMAG2_v3 and is a compilation of data from airborne, shipborne, and satellite measurements (Fig 1). However, the resolution of this map is limited by the spacing between these measurements.

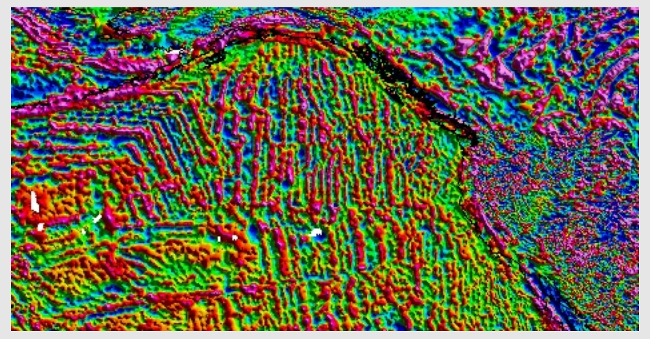

FIG 1: EMAG2v3 showing the west coast of the United States and Canada. The stripes are magnetic lineations due to sea-floor spreading.

Credit: NOAA NCEI

To improve its magnetic reference models and maps, NOAA introduced ***CrowdMag***, a citizen science project that harnesses data contributed by the public through a mobile app that utilizes the magnetometers embedded in modern smartphones. But because the magnetometers in smartphones are of lower quality and thus influenced by surrounding magnetic interference, the collected data is extremely noisy. To overcome this challenge, a type of deep neural network known as an autoencoder (AE) is employed to denoise the data. Most land mapped in EMAG2_v3 are based on sparse observation from aircraft and may be missing many features that are seen by *CrowdMag* on the ground, motivating the effort to denoise the data.

2. Methods

Before using the autoencoder to denoise *CrowdMag*, whose noise is visible in Fig 2 below, it must be optimally trained. This is done by intentionally adding noise and masking to pre-existing EMAG2_v2 data to train the AE, which works by continuously minimizing the reconstruction loss against the corrupted tiles. This training stage ensures denoising task generalization and trustworthy AE performance before application to *CrowdMag* data.

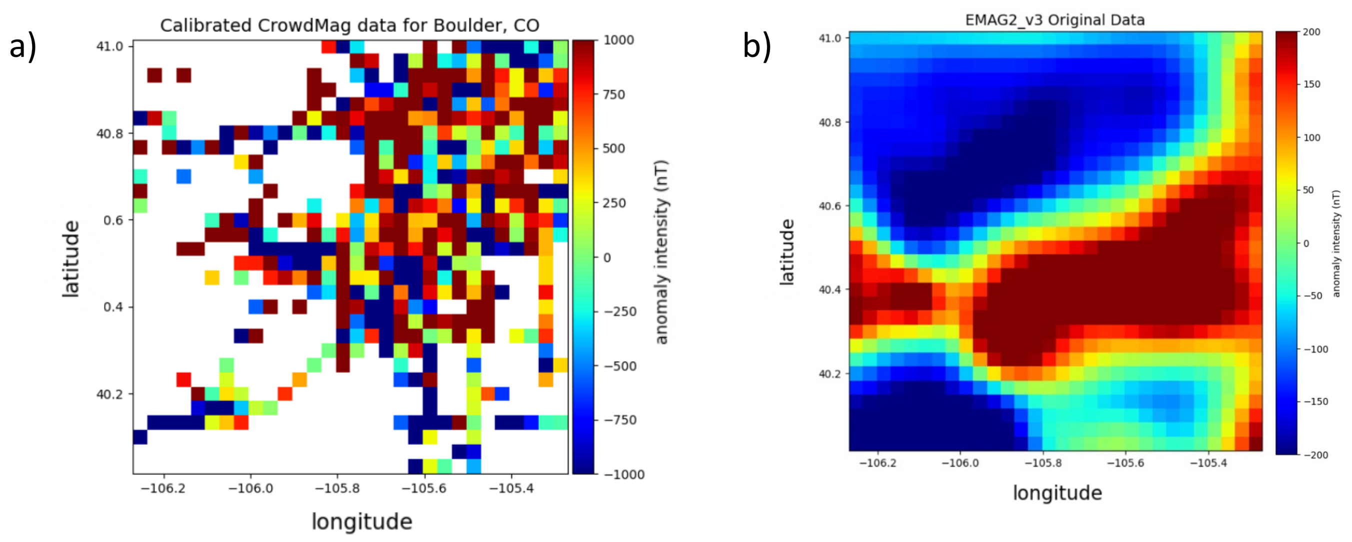

FIG 2: Sparseness and noise level of CrowdMag data (a) contrasted next to high quality EMAG data (b). To train AE, noise and masking is added to EMAG data to benefit denoise task model generalization as seen in the input step of Fig 3.

3. Tuning the Autoencoder

To denoise the dataset, the encoder (Fig 3) takes advantage of the structure of the data to transform the input into a meaningful lower dimensional representation and extract its most important features to then compress it to this dimension. To guarantee a reliable performance, its hyperparameters are optimally adjusted and performance measured by visual comparison of the original EMAG2_v3 data to its reconstruction (Fig 4). These hyperparameters are manually configured settings that play a crucial role in determining the model's behavior, affecting both its training process and its ability to generalize well to new data. The results of manual hyperparameter tuning are:

Hyperparameter	Candidates	Results
# of epochs	20, 30, 40, 50	40
# of hidden layers	1 or 2	1
Loss Function	MAE[1] or MSE[2]	MAE
Optimizer	SGD[3], adam[4]	adam

Hyperparameter	Candidates	Results
Input Size	120x120, 240x240km	120x120
Encoding Dimension	32, 40, 50, 64, 96	50
Randomization	100, 150, 200	150
Masking	25%, 50%, 75%	50%

[1]Mean absolute error, [2]mean squared error, [3]stochastic gradient descent, [4]adaptive moment estimation

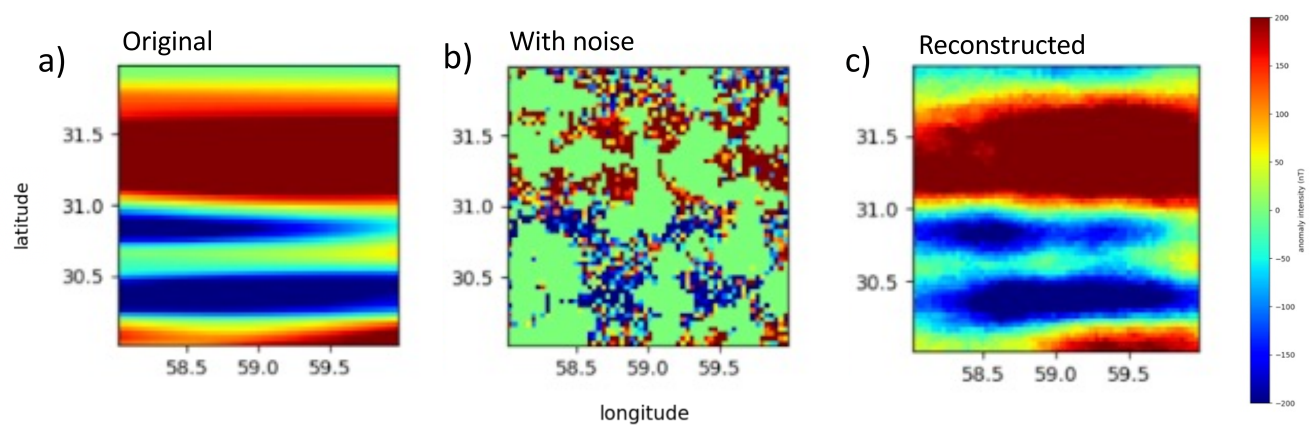

FIG 4: Original EMAG data (a), the same data with intentionally added noise that is fed into the autoencoder (b), and its reconstruction (c). Visual comparisons are made between the 1st and 3rd plot to measure performance.

4. Results on CrowdMag

Hyperparameters are adjusted until the outcome of the reconstruction is visually comparable to the original, as seen in Figure 4. After manually tuning each of the hyperparameters, the optimally trained AE can finally be applied to the noisy *CrowdMag* data. Figure 5 presents a plot of the results for denoising *CrowdMag* in major cities using the hyperparameters decided on above. More work remains to be done to finalize the concluded optimal hyperparameters above, as well as quantify performance alongside these qualitatively performant comparisons.

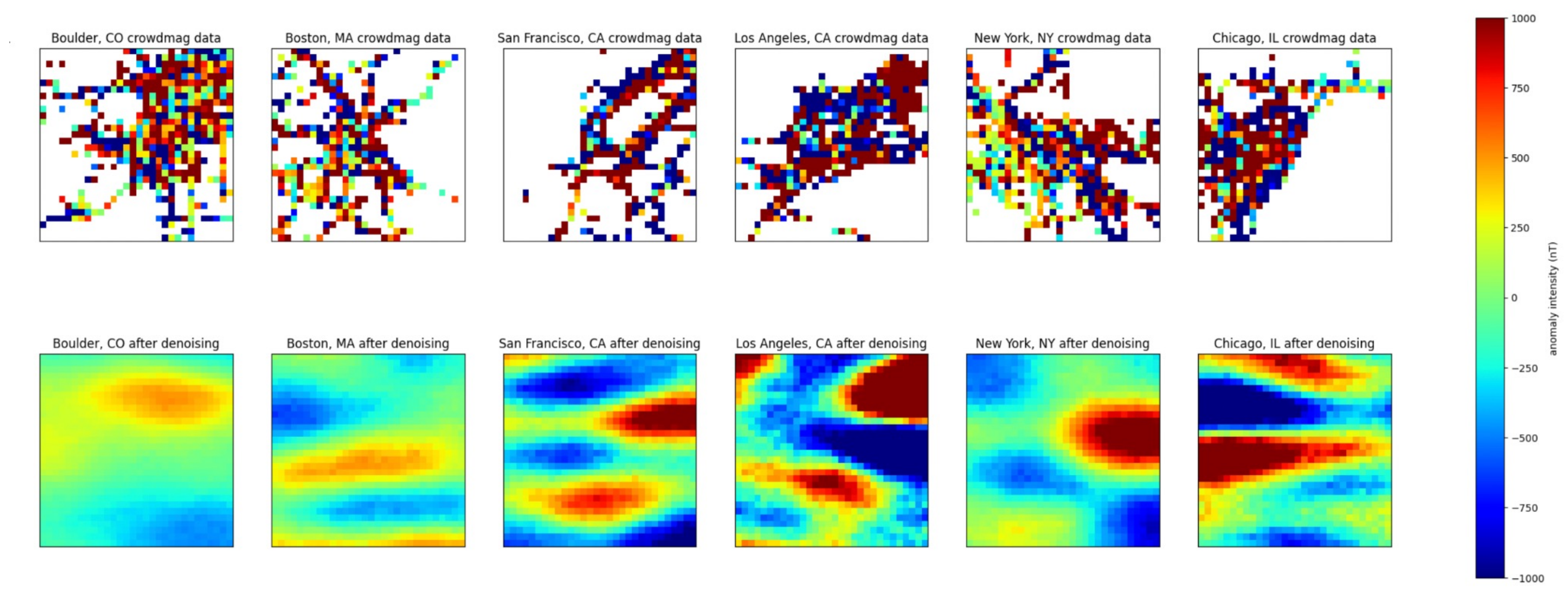

FIG 5: CrowdMag data in major cities and its reconstruction using the optimally tuned AE.

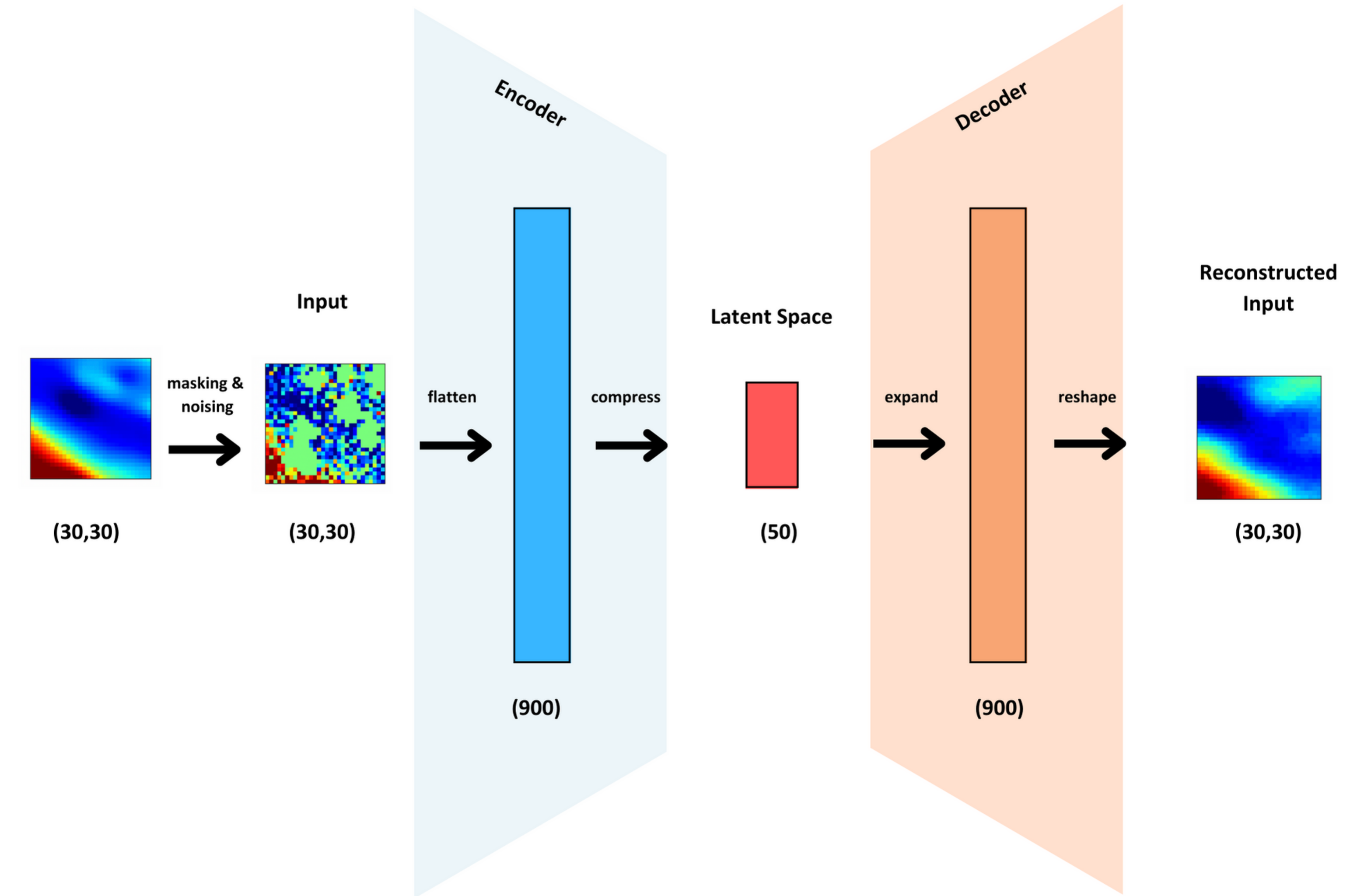

FIG 3: Autoencoder architecture. The AE takes the intentionally noised EMAG data as input and creates the reconstruction seen on the right without access to the original on the far left. Qualitative and quantitative performance assessments are made by comparing the plot on the left and the plot on the right.

5. Future Work

1. **Distributional Similarity**
   - Quantify similarity of original to reconstructed data (Fig 6) using statistical or ML methods (KL divergence, Wasserstein metric, etc)
   - Create loss function that considers distributional similarity
2. **Other Cross Validation**
   - Use RandomSearch and/or GridSearch to confirm hyperparameter decisions
3. **Apply AE to other noisy datasets**
   - Other fields contain noisy datasets that the AE can be extended to.

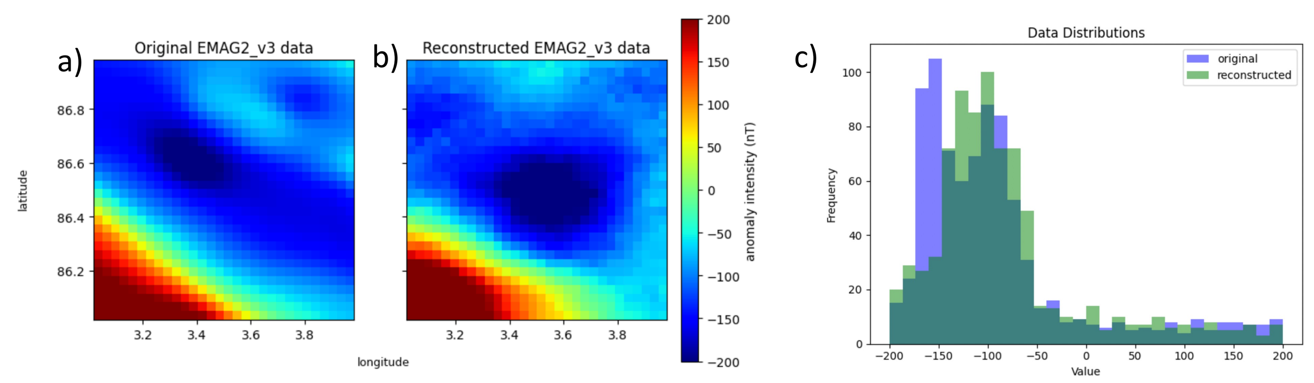

FIG 6: The histogram (c) shows the data distribution of the two plots shown on the left, the original EMAG data (a) and its reconstruction using the autoencoder (b). An ideal reconstruction would see equal histograms.

6. Resources

Download *CrowdMag*!

7. Acknowledgements

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