## Final Report for Christenfeld Summer Research Fellowship 2024

### ConvNN: Convolutional Nearest Neighbor for Neural Networks (Part 1)

**GitHub Repository:** [Repo](https://github.com/mkang817415/Convolutional-Nearest-Neighbor)  
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### Introduction

During this summer, I had the privilege of working alongside Professor Jeova Farias under the Christenfeld Summer Research Fellowship. Our project focused on developing a deep learning model, leveraging satellite imagery to estimate poverty levels in remote South American communities. The innovative aspect of our research lies in the use of a novel convolutional technique – **Convolutional Nearest Neighbor (ConvNN)** – that aims to increase the accuracy of images classification by considering the relationships between pixel and its nearest neighbors rather than just adjacent pixels.

### Objective

The main goal of this project was to create a deep learning model that could be employed in satellite imagery classification, ultimately to aid in poverty prediction. By focusing on the relationships between the center pixels and their nearest neighbors, the ConvNN approach aims to improve accuracy, providing a more wholistic learning of the image data. Our hypothesis was that incorporating a broader context within the images, especially analyzing neighboring structures and landmarks, would significantly improve traditional image recognition processes.

### Methodology

#### Implementation and Testing

The initial phase of the project was dedicated to implementing and testing the ConvNN model on simpler datasets before applying to the poverty prediction. This approach allowed us to validate the model’s effectiveness and refine the technique.

1. **1D Convolutional Nearest Neighbor (Conv1d\_NN):**
   1. We began by implementing ConvNN for 1D images using the MNIST1D dataset, a 1-dimensional representation of handwritten digits. The model underwent rigorous testing, yielding promising results. Although the standalone Nearest Neighbor model didn’t outperform traditional convolutional networks, a hybrid model combining both regular convolution and ConvNN techniques showed significant improvements in performance. This combination demonstrated that our model could effectively learn and leverage the relationships between central pixels and their nearest neighbors.
2. **2D Convolutional Nearest Neighbor (Conv2d\_NN):**
   1. After validating the 1D model, we transitioned to implementing ConvNN for 2D images, encompassing both grayscale and RGB images. Our 2D implementation mirrored the functionality of traditional convolutional layers in PyTorch but with added customizability – such as changeable channels, pixel shuffle/unshuffled capabilities, and varied sampling methods (all samples, random sampling, and spatial sampling).

#### Model Variants

We developed multiple ConvNN variants to explore different sampling strategies:

* **Conv1d\_NN:** All samples and random sampling for 1D data.
* **Conv1d\_NN\_spatial:** Spatial sampling for 1D data.
* **Conv2d\_NN:** Random samples and random sampling for 2D data.
* **Conv2d\_NN\_spatial:** Spatial sampling for 2D data.

#### Evaluation

We tested the 2D ConvNN models on widely used datasets such as MNIST, Fashion MNIST, and CIFAR10 for both classification and denoising tasks. The results were encouraging; however, the traditional convolutional models would often surpass the different model variants in terms of performance.

### Future Work

This research marks the first phase of a broader project: **Poverty Prediction Deep Learning Model**. Moving forward, we aim to refine our ConvNN models throughout the 2024-2025 academic year, focusing on optimizing their performance for various image processing tasks. Our goal is to transition into the second phase of the project – applying the ConvNN technique to predict poverty levels using satellite imagery. We anticipate completing both phases by the end of the 2024-2025 school year.

### Conclusion

The ConvNN project has laid a strong foundation for new convolutional techniques in deep learning, demonstrating the potential for enhanced image classification accuracy. We are excited to continue this work and explore its application in real-world scenarios, particularly in assessing poverty levels in underdeveloped regions. For further details on our methods and code, please refer to our GitHub repository linked above.

### Acknowledgements

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