Accelerated Deep Neural Network Strategies for Rapid X-Ray Diagnosis

Improving healthcare diagnostics with limited data and lean machine learning.

Overview

This solution compares two deep learning methods for chest X-ray diagnosis: one using a proven VGG16 transfer learning model (current state-of-the-art), and another using few-shot learning that requires only ***8 examples per category*** (e.g., positive or negative for pneumonia). Despite the minimal data, the few-shot approach achieves similar accuracy while **drastically cutting training and response times** —making it an efficient, cost-effective solution for urgent healthcare settings.

Key Highlights

- 🔢 Minimal data requirement: *on each training run, only* **8** *examples per classified category are needed to achieve competitive performance.*
- 🚀 Rapid Training: *Time spent training model is reduced by* **58x** *compared to traditional models for this task.*
- ⏱️ Fast Inference: *Near-real-time diagnosis with significantly reduced response times with model predictions.*
- 💰 Cost-Efficiency: *Lower computational demands result in reduced operational costs.*
- 🔄 Adaptable Solution: *Ideal for fast deployment in emergency and resource-limited healthcare settings.*

How It Works

My approach leverages a meta-learning algorithm known as Prototypical Networks, which fall under the umbrella of few-shot learning (FSL). FSL allows ML models to create predictions having “seen” very limited amounts of data (a common practical obstacle in the field).

Simplified, imagine two students preparing for an exam. The first has access to a comprehensive textbook, containing thousands of pages of detailed info. This student spends countless weeks studying every nuance.

In contrast, the second is provided a concise study guide with a particular number of key examples (“support”) and practice questions (“query”) during each study session. In the case of my solution, that number is 8 of each. Despite reviewing less material, this student specifically focuses on the essential patterns and concepts, and engages in a handful of brief study sessions (“episodes”) ...

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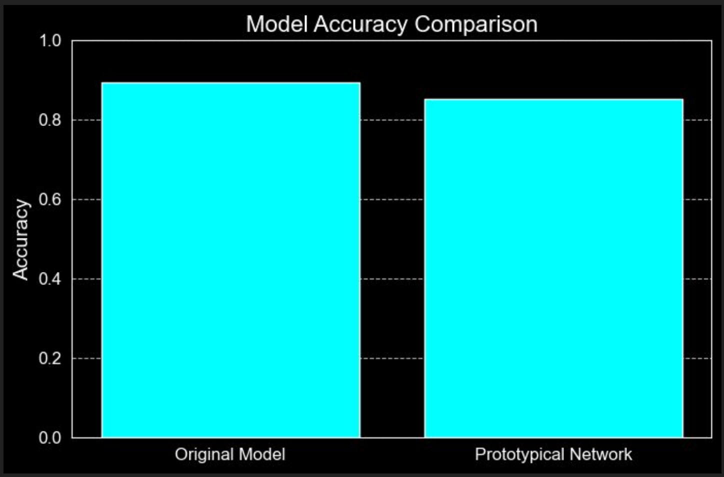
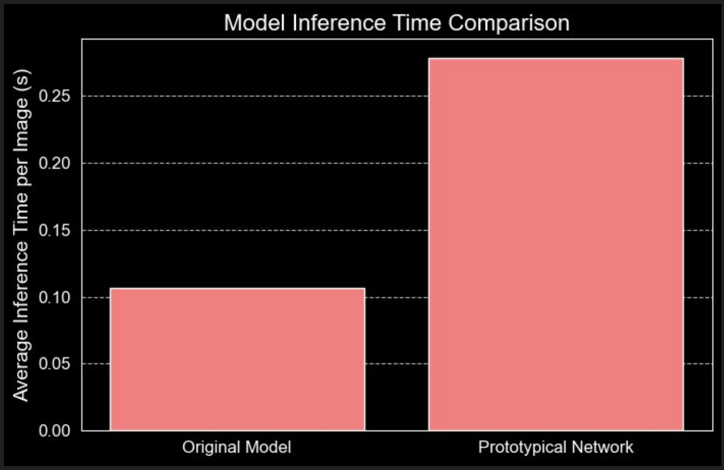
How It Works (Continued)

Finally, the 2 students arrive at the day of the exam. Surprisingly, both students complete the exam in roughly the same amount of time, and even more surprisingly, the second student earns a near identical exam grade to the first student. Despite not having the full textbook, and studying for <2% of the time the first student did, the second student achieves nearly identical results. That "second student" is the proposed Prototypical Network.

Initial Prototypical Network Results

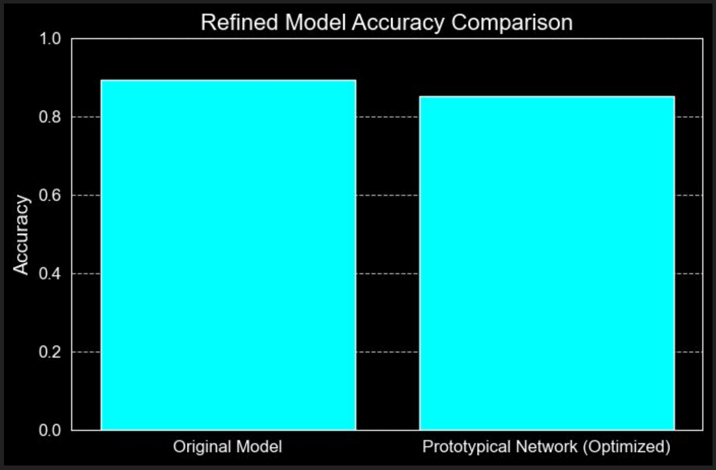
High accuracy and fast training were accomplished with the initial iteration. However, as shown below, the average time the prototypical network spent diagnosing chest images took twice as long as the traditional model on a per-X-ray basis. This was a problem.

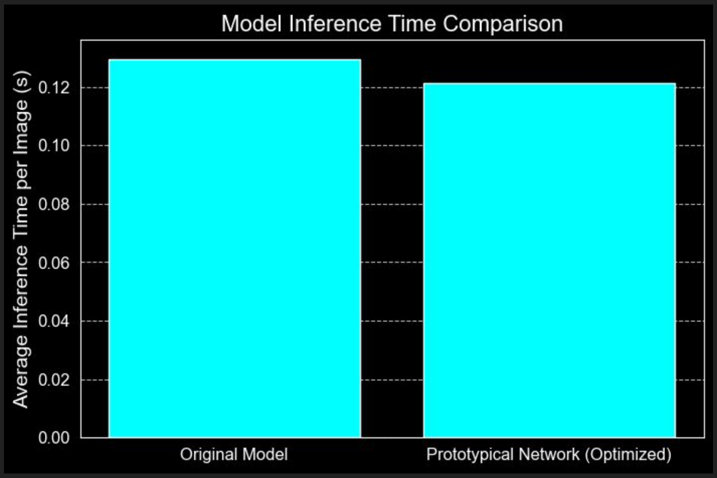




Model Optimizations

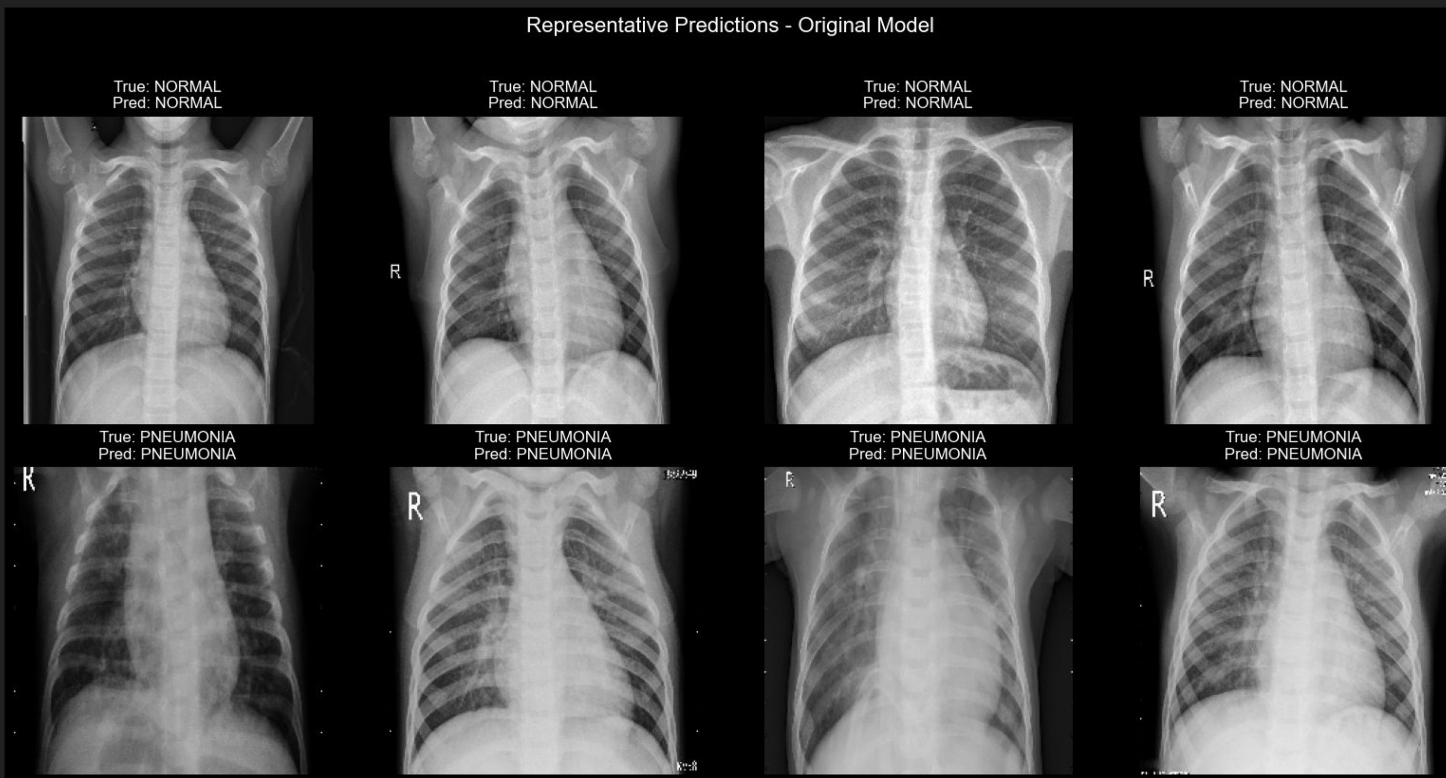
Without retraining, adjustments and optimizations were made to the prototypical model's inference "flow" that reduced time spent performing redundant operations, successfully resulting in both comparable avg. inference time and accuracy.

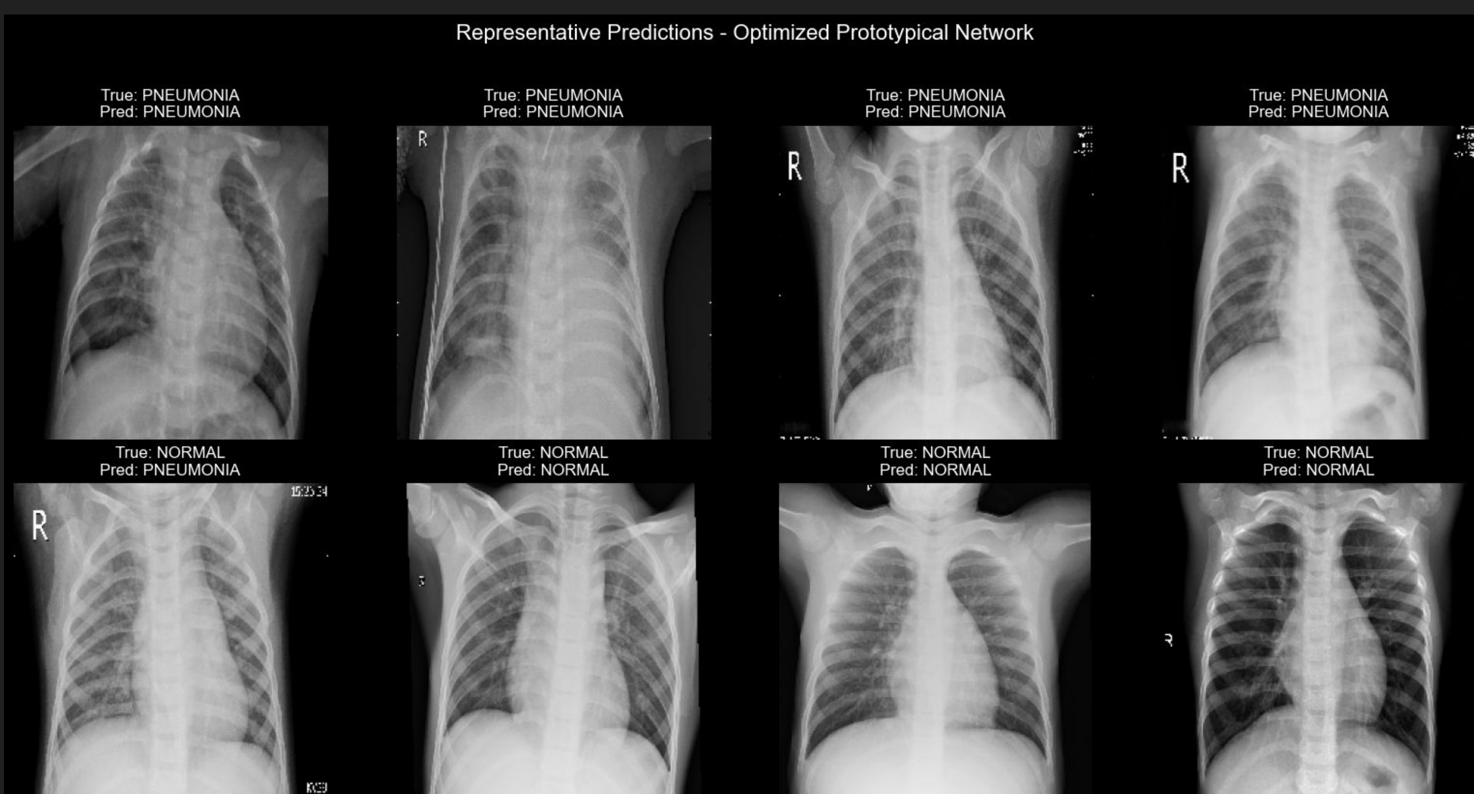




Model Predictions, Visualized

Both the prototypical model and the baseline model made an impressive amount of accurate predictions, as visualized below alongside a sampling of inputted X-rays.





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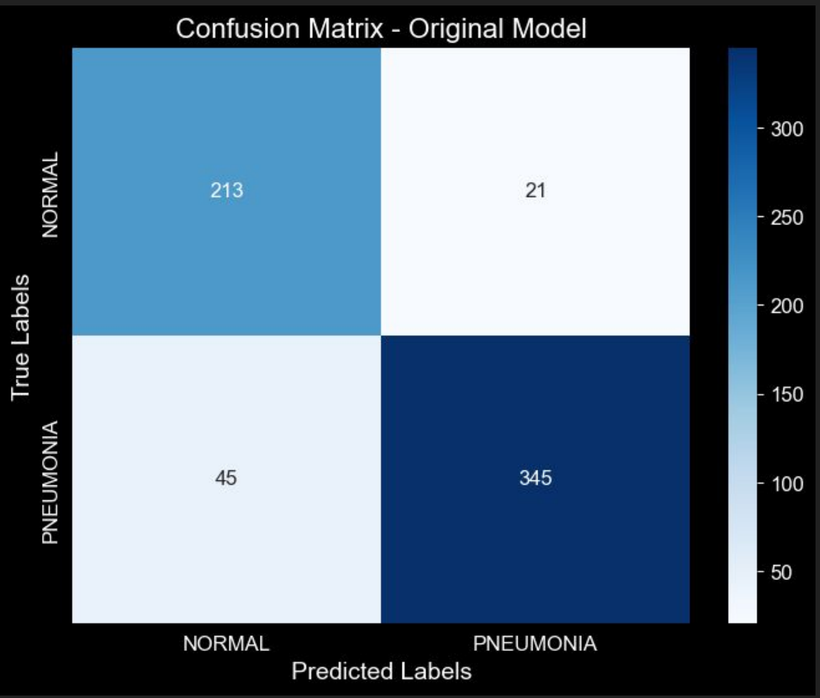
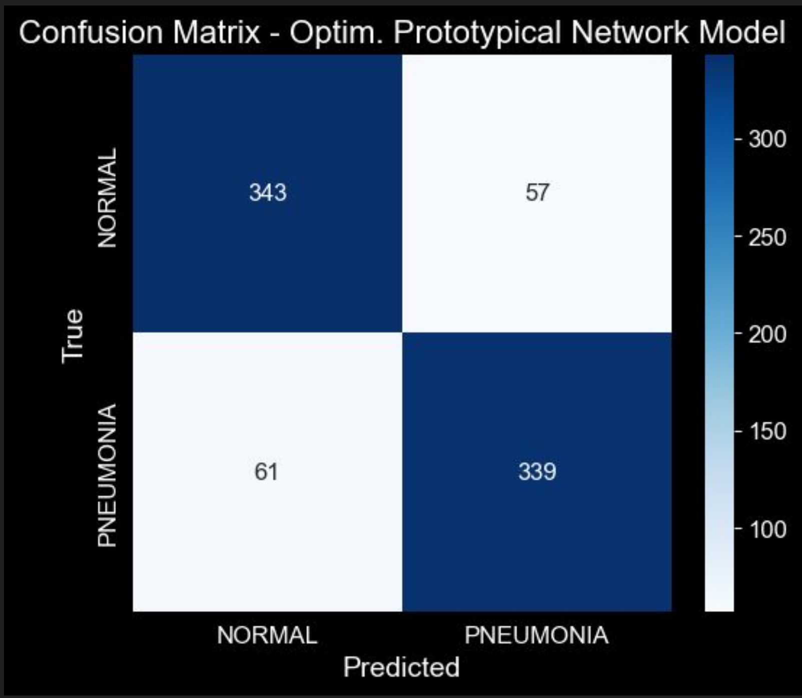
Visualized Predictions (Continued)

Overall predictive performance for each model can be viewed in the 2 tables below. Top left and bottom right squares are desirable, true predictions, and the remaining squares represent predictive errors (false positives or false negatives).





Impact and Use Cases

This FSL approach not only considerably reduces training time but also enables near real-time inference, making it ideal for rapid model updates in critical healthcare situations. For instance, during early stages of a pandemic such as the COVID-19 outbreak, hospitals faced significant challenges due to limited labeled data for various chest X-ray abnormalities (such as pneumonia, pulmonary edema, and tuberculosis). A similar approach could have been deployed quickly to update diagnostic models with minimal new labeled data, accelerating accurate diagnoses and patient triage in challenging, resource-constrained settings.

Conclusion

The proposed approach delivers competitive diagnostic performance with a fraction of the training time (from 1047 seconds down to 18 seconds) and faster inference speeds, making it a highly efficient and adaptable tool for real-time chest X-ray diagnosis in fast-changing, data-scarce environments

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All work was produced and pursued as an independent research initiative of mine.
Code available via https://github.com/btomlinson237/FewShotLearningForPneumonia