CSCI 597J Project Proposal

Matthew Carter, Christopher Drazic, Ivan Chuprinov, Alex Gavin, Raleigh Hansen

1. **What are you trying to do? Articulate your objectives using absolutely no jargon.**
   Our aim for this project is to improve the efficacy of computer aided detection (CAD) by showing how manipulating data affects the performance of a demonstrated baseline pneumonia detection system. We will be using ResNet, a deep neural network architecture specifically designed to classify images based on their features. We intend to show that even if the size of a quality dataset is a limiting factor, using data augmentation techniques like rotating images, increasing the contrast of images, etc. we can improve the performance of our model. To demonstrate this increase in performance, we will take three different perspectives on the data being fed to our model. This will manifest by accurately classifying new data, without being overly confident in its classifications.

2. **How is it done today, and what are the limits of current practice?**
   Current models used in pneumonia classification have either been trained on an unbalanced, unmodified dataset of chest x-rays or trained on a dataset where some percentage of x-ray data has been augmented or altered by preprocessing. Research projects of this nature are distinct from one another in that they often follow different methodologies and use different underlying architectures. This leaves little room for a clear comparison between the effectiveness of using or neglecting preprocessing methods on the data for this task. Additionally, it is not clear in current work which augmentation and preprocessing techniques may lead to better performance for a model given this learning task and which may hinder it.

3. **What's new in your approach and why do you think it will be successful?**
   Our approach will provide new insight into the effectiveness of specific preprocessing techniques on x-ray images to perform classification which may aid in making a formal diagnosis of some condition. Specifically, our work tackles the issue of how to alter a limited dataset to achieve better performance from a pneumonia classification model. There exists some evidence in research of various preprocessing techniques which have improved model performance. We can go forward with this knowledge and dive deeper to examine the specifics of measuring performance increase in relation to the type of data altering that has occured. We believe our approach will be successful because we will not only be leveraging existing work but also can apply a very clear, methodical approach to distinguish which techniques help or hurt performance given the same underlying architecture.

4. **Who cares? If you're successful, what difference will it make?**
   If we are successful, the deep learning community will have gotten one step closer to solving the problem of automatizing medical diagnosis of pneumonia. That is important because it would be able to reduce the human error in the diagnosis process, and it would allow places with radiological equipment but no expert to more readily detect pneumonia. If our model succeeds at predicting pneumonia using the chest X-ray images, we could help the places that have no radiology experts. Also, since medical data is sparse due to patient confidentiality, being able to demonstrate that augmentation we are going to apply can be effective in improving generalization would be quite useful.

5. **What are the risks? What are probable ways you could go wrong?**
   This project and the data that we'll be using for it include some risks from both the deep learning aspects as well as the medical aspects. Regarding deep learning, if we attempt to implement an overly complicated model, we could run into issues near the deadline of the project if the model is not completed or if issues arise while trying to train the model. Additionally, lacking access to resources necessary for training such as time and computing capabilities may inhibit us from exploring all augmentation techniques we wish to evaluate. As for the medical aspects, possible issues include our predictions not being medically accurate if we train and test on a medically inaccurate dataset.

6. **How will you know if you're on track?**
   If we were to train a simple CNN first and get a good baseline, we should get a clear depiction of our architecture before we can fine tune it for the specific images we are trying to classify. We can also confer with other groups who are utilizing a CNN architecture to discuss any shortcomings we have in the design phase. After we can sufficiently prove that we can detect different types of pneumonia, another good way to check our model is on track is to use less clear images to further increase the robustness of our model so that it is less prone to overfitting. This will allow our model to classify images that are less obvious to the naked eye. Other models that have incorporated our proposed, or similar structure used on medical sets can be a good metric to base our understanding of how well our model is doing and where we can explore for tweaks.

7. **What baselines will you use to compare against your method(s)?**
   There are various papers that outline several experiments conducted relating to the classification of chest x-rays. Within these papers, there are several systems that have shown high accuracies and promising results. As we're going to be implementing a variation of ResNet9, we will use the original work done on ResNet9 as a baseline to improve on. Other baselines include similar implementations such as ResNet18, RestNet50, and DyNet. These more complicated implementations will provide a proving ground to test various iterations of our model in order to deem our changes as improvements.

8. **What data do you plan to use for this problem?**
   We have decided upon a dataset of 5,863 chest x-ray images containing jpegs pre-labeled as viral pneumonia, bacterial pneumonia, or no pneumonia. The dataset has been validated by two physicians for label consistency and accuracy as well as scrubbed to remove any unreadable or low resolution chest x-rays to allow for a more concise dataset. We will then augment the core dataset by performing operations such as zooming, rotating, increasing contrast, increasing brightness, and translating on the images in order to increase its size.

9. **If this is a continuation or extension of an existing project, state exactly where you are so far (significant new progress is required)**
   N/A