Implementing Complex Valued Neural Networks

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Abstract

1 Introduction

Complex valued neural networks (CVNNs) offer several potential advantages over real valued neural networks (RVNNs). By incorporating both phase and magnitude in each value, CVNNs allow for a richer representation of data. This increased information content in each input and parameter can lead to a reduction in the number of parameters, subsequently lowering the likelihood of exploding and vanishing gradients while also reducing the need for regularization. Furthermore, some types of data are naturally suited for representation using complex numbers.

CVNNs hold great promise in domains where complex values are already extensively utilized, such as quantum computing and signal processing. Outputs from Fourier transforms and other complex representations can be directly fed into the network, eliminating the need to separate or remove information from each value as required with RVNNs. Additionally, certain complex transforms and filters can be applied to images, thereby reducing the need for convolutions in image classification tasks[1].

Despite these advantages, many popular neural network frameworks, such as PyTorch and Keras with TensorFlow, offer limited support for complex valued neural networks by default. Nevertheless, TensorFlow does provide support for complex tensors, which enables the implementation of CVNNs by defining custom layers. In this project, we take advantage of this functionality to explore the potential of CVNNs further.

2 Related Works

Akira Hirose (2012). ***Complex-Vaued Neural Networks, 2nd Edition***

This book provides an overview of complex valued neural networks and some applications. Much of the implementation is based on concepts from this author's works.

Manny Ko et al. (2022). ***CoShNet: A Hybrid Complex Valued Neural Network using Shearlets*.**
arXiv: `2208.06882 [cs.CV]`

In this paper they explore shearlets and CVNNs in image processing to reduce the need for convolution, increase efficiency and improve performance. This is an excellent demonstration that CVNNs are worth investigating.

[1] See Ko et al. 2022

Course project for UBC CPSC 440/540, April 2023.

Ryan Yu et al. (2022). ***Biologically Plausible Complex-Valued Neural Networks and Model Optimization*****. Ed. by Ilias Maglogiannis et al. Cham**

The primary motivation for this project was the potential of CVNNs to more accurately approximate biological networks. The paper investigates CVNNs, which are designed to be more similar to biological neural networks than their real-valued neural network (RVNN) counterparts, demonstrating superior performance in certain tasks. However, the paper's main drawback lies in its reliance on gradient descent as a training method, as this is likely an unrealistic learning mechanism for biological systems (Hinton 2022).

3 Description

4 Experiments

4.1 MNIST

To test the implementation we do a trial run on MNIST data set to verify the implementation is functioning. For the real neural network we use 32 filter 4 by 4 kernels with softmax output layer. The complex network has 16 filters of 4 by 4 kernels to halve the number of parameters. CVNNs do not offer much benefit in a simple case like this, but is a convenient test set.

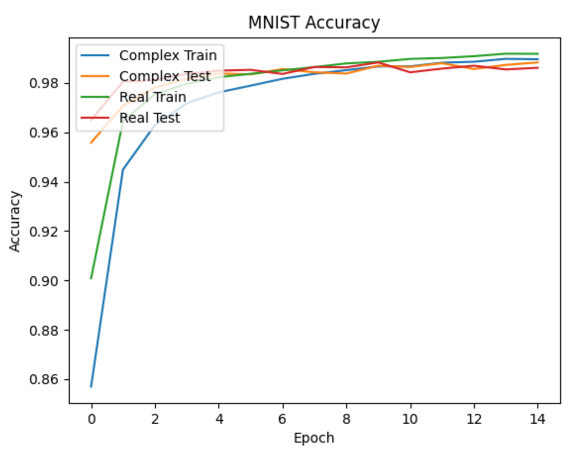

Figure 1: As expected we get similar performance.

4.2 Fashion MNIST

We also tested training on the 2D fourier transform of Fashion MNIST data set (Xiao, Rasul, and Vollgraf 2017)

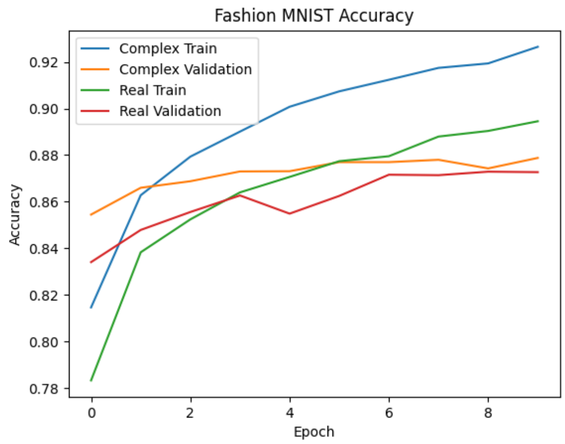

Figure 2: For complex case we used fourier transform values directly.

4.3 Audio

4.3.1 Dog versus Cat Audio

After training on images we downloaded a simple dataset of cat sounds vs dog sounds using complex valued outputs of `tf.signal.stft(waveform)` as inputs to a convolutional neural network.

Data set here `https://www.kaggle.com/datasets/mmoreaux/audio-cats-and-dogs`

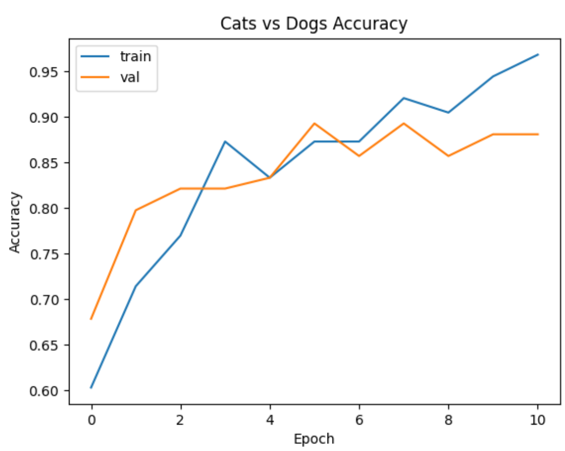

Figure 3: Given the small size of the data set we overfit quickly.

4.3.2 Emotion Classification

Using a subset of the Toronto emotional speech set (Pichora-Fuller and Dupuis 2020) we trained a complex valued neural network on the spectrogram (complex valued) to categorize audio into classes based on predicted emotion of the speaker.

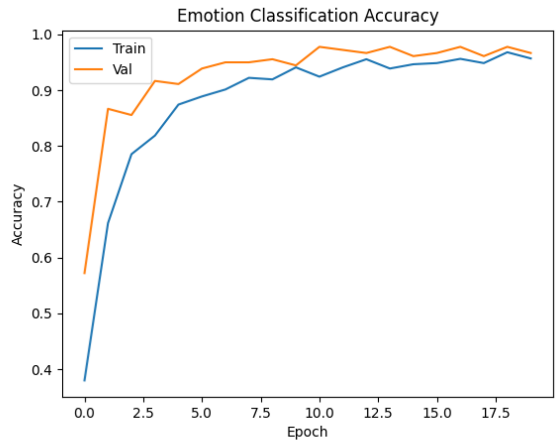

Figure 4: We achieved very quick convergence.

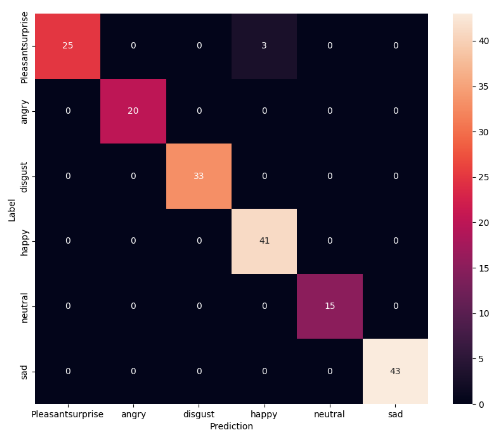

Figure 5: The model sometimes confused happy with pleasant surprise.

References

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