CS-445/545 Machine Learning Final

CNN versus SVM

Will Farris, Ajay Babu Gorantla, Gilbert Grundy, Kuldeep Akbari, Joel Williams

https://github.com/sciwizard/ml-final-project

1 Roles

- **Joel Williams** - Abstract, introduction, Matplotlib plotting, SVM vs CNN experimentation, LaTeXification
- **Will Farris** - Implemented SVM, wrote up analysis of SVM performance & conclusion section
- **Ajay Babu Gorantla** - CNN implementation, experimentation, and model analysis
- **Kuldeep Akbari** - Contributed to CNN, analyzed different models, documentation
- **Gilbert Grundy** - Contributed on documentation and SVM, and comparing SVM vs CNN performance

2 Abstract

Machine learning is a notoriously data-hungry field within computer science. Often, the effectiveness of a machine learning program hinges on the volume of data fed into it. Choosing a model which performs well under data constraints, then, can boost a model's performance when data is scarce. Convolutional neural networks (CNNs) are used by many modern image processing applications to classify images. Support vector machines (SVNs) can also be used, however CNNs tend to be used more commonly. Our research pits CNNs and SVNs against one another, to see which one performs classification better on a subset of the MNIST fashion dataset using various performance metrics. We first optimize a CNN and an SVM by tweaking

various hyperparameters, and then compare their relative performance as training data size scales.

3 Introduction

Machine learning algorithms for image classification have been steadily gaining wide advances since their inception, due to ever increasing compute power and the continuously accumulating amount of data on the internet. Researchers in the 1960s conceived of using Markov chains to perform contextual classification of an image using binary array values [1]. In 1968, researchers also explored using discrete probability trees for image classification, producing a maximum-likelihood estimation [2]. In 1995, Vladmir Vapnik at Bell Labs invented support vector machines with binary classification [3]. The usual approach for multiclass classification for SVMs is to break the classification into multiple binary sub-problems. CNNs are evolutionary descendents of perceptrons and multilayer neural networks. The first generation of CNNs were based off of the “neocognitron”, created by Kunihito Fukushima, who published the results in *Biological Cybernetics* [4]. This helped spur the Deep Learning revolution, especially in regards to the widespread use of machine learning algorithms for internet image classification.

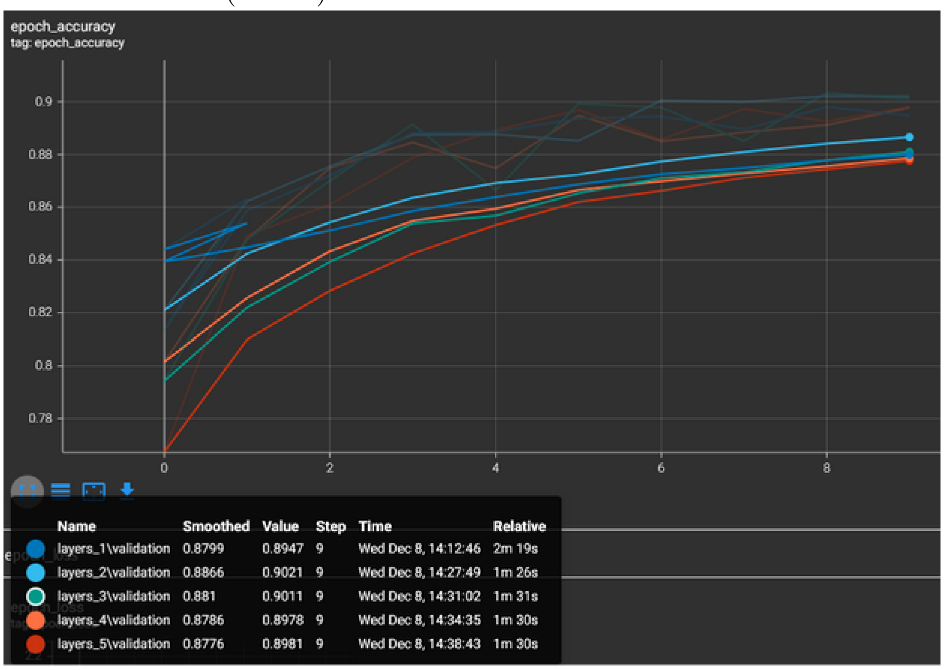
Our research pits these two learning algorithms against each other. Our intention is to first optimize each algorithm individually, by varying hyperparameters on each to maximize their accuracy performance. Then we contrasted the optimized models, the CNN and the SVM, to see which performs better with different sized training sets. With CNN, we'll vary the number of hidden layers, the learning rate, and activation function. We kept our momentum rate constant at 0.2 . With the SVM, we varied using different kernels between linear, sigmoid, 3rd order polynomial, and radial basis function (RBF). Since both algorithms are extremely architecturally different, for instance the SVM has no concept of learning rate or momentum, direct comparisons between the two by varying hyperparameters isn't the most productive experimentation method. Instead, we compare accuracy between our optimized hyperparameter models, contrasting their performance on controlled size training sets. We hope that this will provide future machine learning practitioner intuitions regarding which algorithm to use given a particularly sized training set.

4 CNN Analysis

For the analysing of the CNN we are varying the number of hidden layers, activation functions, and the learning rates. The CNN uses 10 epochs of training data and a batch size of 100.

4.1 Depth

First, we compared the accuracy of the CNN with a varied amount of hidden layers with 32 ReLu nodes each. We set the learning rate (0.1) and activation function (ReLU)



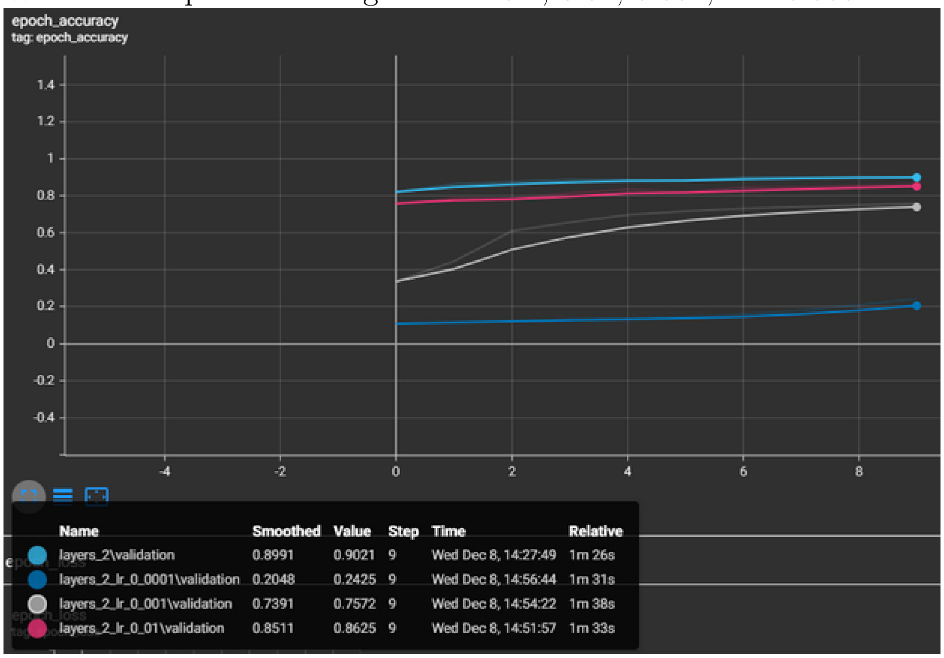
As we can observe, there is not much difference in the final accuracies for change in the number of hidden(Dense) layers.

Among the different models(each with a different number of hidden layers),after 10 epochs, the model with 2 hidden(Dense) layers had the best accuracy on the validation set i.e. 90.21

We wanted to analyze how that above best(in terms of accuracy) model would behave with a change in the learning rate. In the next section, we talk about that behavior.

4.2 Learning

We then compared training rates of 0.1, 0.01, 0.001, and 0.0001.



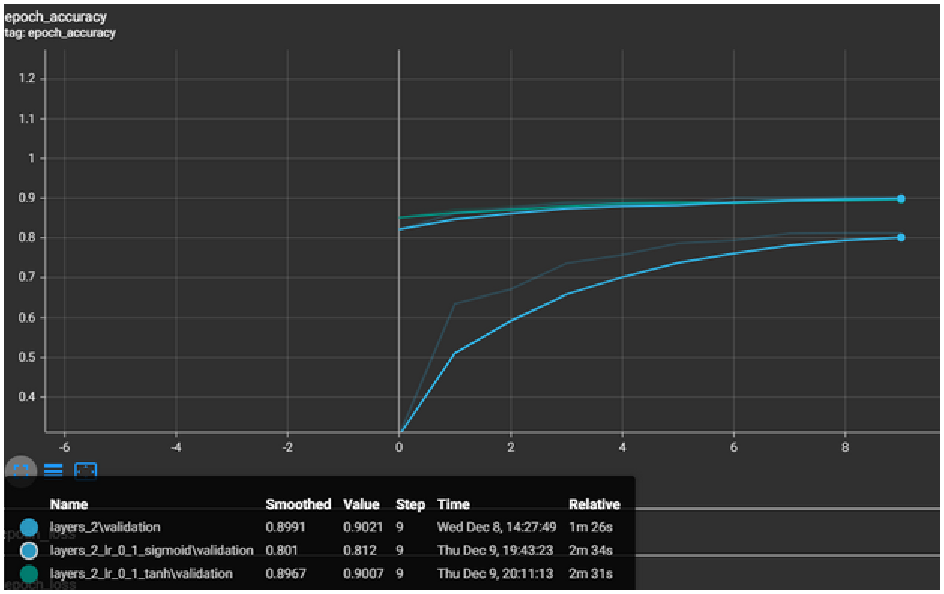
We can clearly observe that, with increase in the learning rate the accuracy is also increasing. The lowest accuracy was obtained with learning rate =0.0001 and the highest accuracy was obtained with learning rate = 0.1

So, among the different tested models with change in network size(depth) and change in learning rate, the best model we found out was the model that has 2 hidden(Dense) layers and with learning rate 0.1

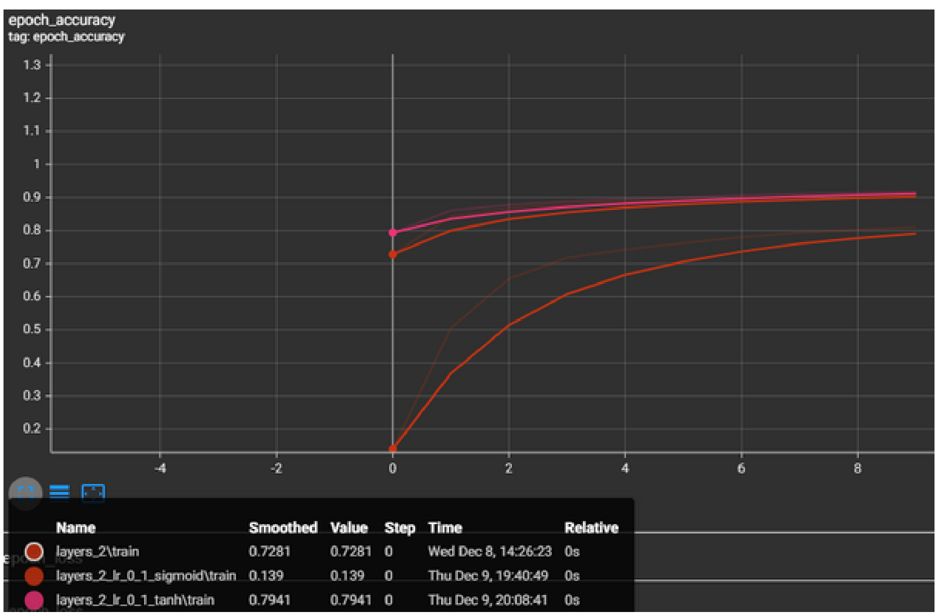
Now, we wanted to analyze the behavior of the above model with change in type of activation function. In the next section, we talk about that behavior.

4.3 Activation Functions

Finally, we compared the activation functions of ReLU, Sigmoid and tanh.



From the above plot, we inferred that all the activation functions gave some good results. However, 'ReLU' and 'tanh' played out relatively and considerably better than the 'Sigmoid'. There is a very slight difference between the accuracies of 'ReLU' and 'tanh'.



One interesting observation that we noticed from the above figure is that 'tanh' started off with better training accuracies than the other two activation functions. Although there is a very slight difference in accuracy between 'tanh' and 'ReLU', the latter has better accuracy, the main reason we chose to consider 'ReLU' for further analysis is that it is computationally less expensive than 'tanh'.

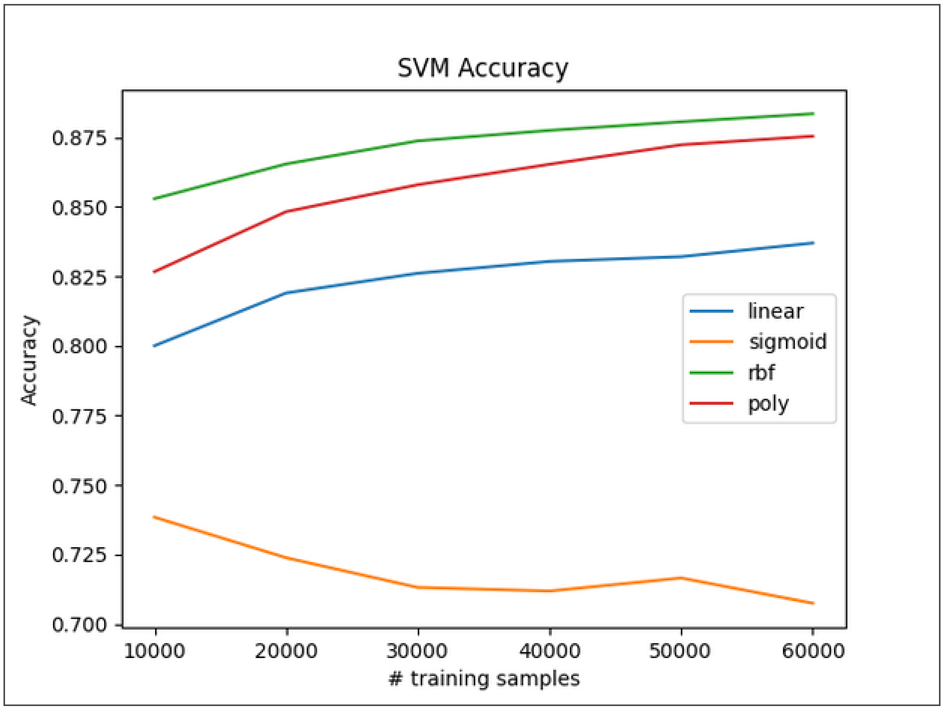
5 SVM Analysis

We implemented a support vector machine using scikit-learn which we then trained on the fashion mnist dataset. We tested the accuracy of three different kernel functions with varying amounts of training data for a support vector machine implemented with scikit-learn. Of the four kernel functions tested, the radial basis function resulted in the highest test accuracy at 88.36% when provided 60,000 training samples. The sigmoid function came dead last, settling at 70.74%, it was the only kernel function that descended in accuracy as the training samples increased. The linear kernel function performed the next worst at 83.7% test accuracy, and the 3rd degree polynomial kernel came in a close second at 87.55%.

5.1 Kernels used

To choose the most performant SVM we compared the relative performance of the following several kernel functions. As different kernel functions are suited for different distributions of data, we wanted to choose a kernel which would be most performant on the task of image recognition. We compared the performance of the following kernel function: radial basis function (RBF), 3rd degree polynomial, linear and sigmoid. Experimenting with the kernel function used allowed us to choose the best SVM configuration for the task of image classification.

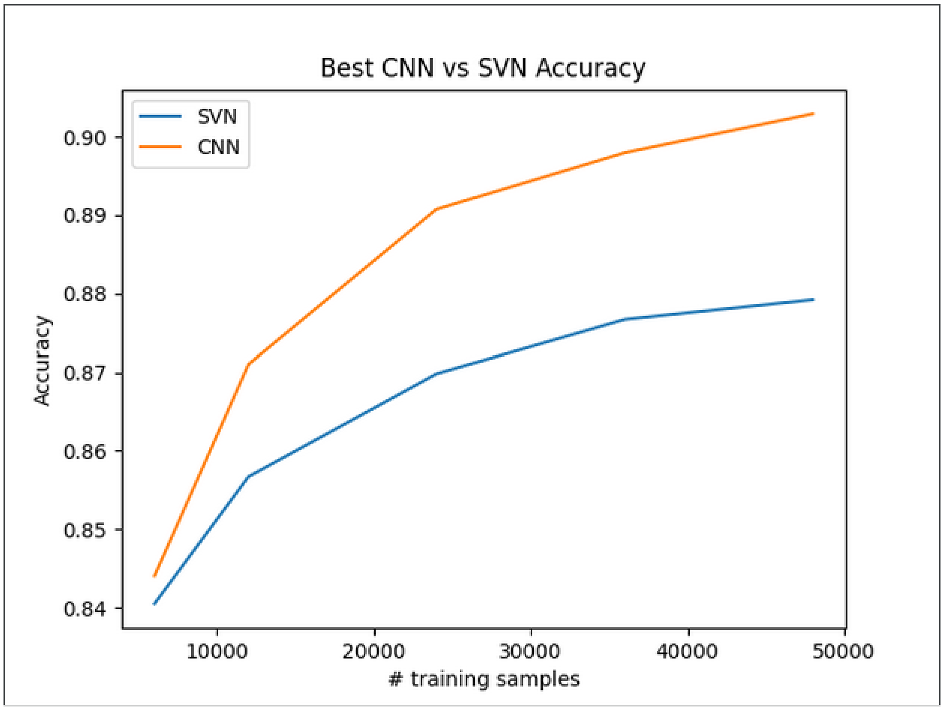
5.2 Results



6 CNN versus SVM Analysis

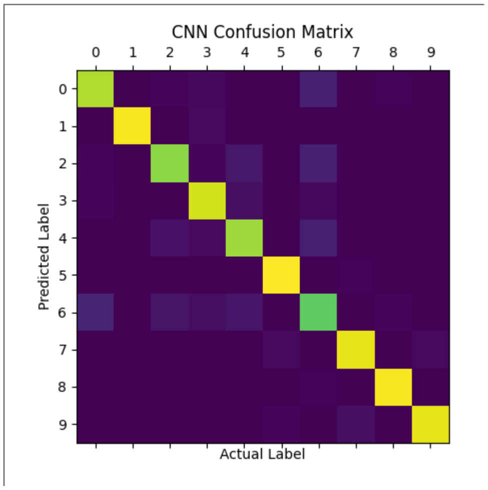
Our CNN model with the best accuracy was with a learning rate of 0.1, an activation function of tanh, 32 nodes on each hidden layer, and two hidden layers. Our best SVM model was using a RBF kernel. In order to compare the two best models we could come up with, we froze these hyperparameters and retrained/refit both models with increasing training set sizes from 6000, 12000, 24000, 36000, and 48000. The CNN had 10 epochs for each training set size and a batch size of 100. The SVM took the direct training samples.

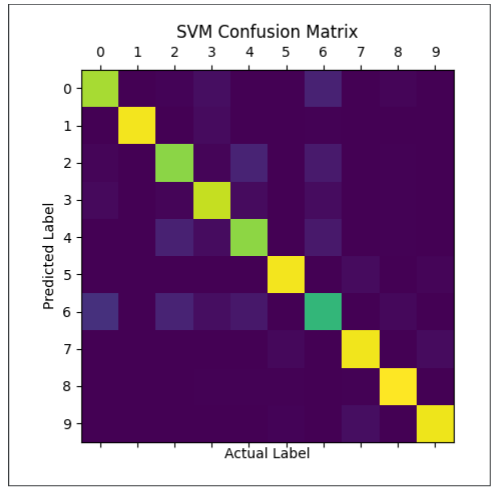
6.1 Training set size change



6.2 Conclusion

As shown in the figures above, our top-performing CNN outperformed our top-performing SVM across all training data sizes. This suggests that, for the task of image recognition, convolutional neural networks offer better accuracy then support vector machines even when heavily constrained by the size of the training set. This comports with current trends in machine learning, where the CNN has become significantly more popular in recent years than the SVM. It's important to note that this comparison only took into account the amount of training data, and did not analyze performance relative to inference or training time. In conclusion, our findings suggest that if constrained by the amount of training data, the convolutional neural network offers superior performance relative to the support vector machine per training example.





6.3 Future Scope

Instead of relying on built in functions from the sklearn library for the SVM's kernel function, further investigation with custom kernel functions may have allowed for some interesting analysis. Additionally, we may have spent some time using different optimizations algorithms for our CNN, such as Adams, and tried different values for the momentum rate of 0.2, and different weight decay values for which we omitted.

References

[1] K. Abend, T. Harley, and L. Kanal. "Classification of binary random patterns". In: *IEEE Transactions on Information Theory* 11.4 (1965), pp. 538–544. DOI: 10.1109/TIT.1965.1053827.

[2] CKCN Chow and Cong Liu. "Approximating discrete probability distributions with dependence trees". In: *IEEE transactions on Information Theory* 14.3 (1968), pp. 462–467.

[3] Corinna Cortes and Vladimir Vapnik. "Support-vector networks". In: *Machine learning* 20.3 (1995), pp. 273–297.

[4] Kunihiko Fukushima and Sei Miyake. “Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition”. In: *Competition and cooperation in neural nets*. Springer, 1982, pp. 267–285.