Determining the Efficacy of Simple Regression and Deep-Learning Models for Application to Resource-Constricted Classification Tasks

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***Abstract*—Pre-trained image classification models work effectively, yet are very large in size. For embedded and other resource-limited applications, it then becomes necessary to use smaller models. This project aims to determine whether neural networks or logistic regression models could effectively classify apparel data. Evaluation results then show that a simple convolutional neural network (CNN) with dropout and pooling layers provides a high validation accuracy of 90% at a size of 1.13MB. The logistic regression model provided an even smaller size solution at 0.03MB although its 85% validation accuracy coupled with its simplicity, would need improvements before it can be considered for real world applications. In both cases, it seems loading a smaller model could be a an effective alternative for low-memory uses. Further work is suggested in maintaining that level of performance and size for more complex images.**

I. Introduction

Embedded applications must be reliable, fast, and secure. Therefore accessing cloud services for model inference is an ineffective solution since there could be network issues, timing delays in requests, and interception during transmission which could lead to stolen data [1]. Instead it is best to store the model on the machine and run inference tasks locally. It is possible to use pre-trained models for inference, yet these models require 16-548MB of space for use [2]. Embedded devices may support anywhere from a few kB to hundreds of MB in storage capacity [3]. Therefore, pre-trained models may be infeasible to use for an embedded application. Then the question becomes whether simpler models offer similar performance at a smaller size. Therefore the project aims to perform image classification using neural networks with a logistic regression model as a base comparison to determine if it is feasible to use these models in resource-limited embedded systems.

II. Background & Related Work

A. Previous Attempts at Fashion Data Image Classification

Image classification for apparel data has been performed using large pre-trained networks including VGG-16, VGG-19, InceptionV3 and a custom CNN with millions of trainable parameters. The data used for evaluating each network included 30 categories of clothing items where each sample is represented using a triple-channel color image. Each image additionally is more organic as it contains the person wearing that clothing item [4]. From the experiment it was found that using pre-trained models offers better results than a custom CNN, yet the difference in performance is small. The data set used is more complex in the sense that each image is very different from another, therefore more parameters are required. Hence in theory, it could be possible to achieve high performance on a simpler data set using less parameters in a smaller CNN architecture. That is where research gap exists that we aim to fulfill by testing whether smaller models can work effectively for simple fashion apparel classification tasks.

B. Existing Developments in Resource-Constricted Learning

The following sections include existing work done to lower the computational burden in embedded applications. Methods to reduce the memory overhead and computation-load in resource-constricted applications include employing quantization and network pruning. Quantized deep neural networks attempt to use less bits to represent neurons and activation outputs. Challenges associated with this approach include difficulty with calculating gradients and ensuring proper gradient flow when very few bits are used for representation. Network pruning involves removing neurons from the network and reduce the complete number of computations performed. Methods for pruning involve removing neurons while tracking the change in the loss function to ensure network performance is conserved. It is evident that prior developments focused on modifying the computational graph itself or how it is encoded and stored at the hardware level. [5]

C. Activation Function Considerations

The following sections include neural network architecture considerations to maintain or improve performance while reducing computational overhead by layer selection.

Activation functions are applied to the output of each neuron to add non-linearity to the model. Without it the model can only learn linear behavior which may be unrepresentative of the data's underlying properties. Selecting the right activation

function then becomes crucial. Activation functions must possess the following properties to be effective:

- Must be differentiable to ensure back propagation can proceed by application of the chain rule.
- Must prevent gradient from vanishing or exploding during loss function adjustment through back propagation. A vanishing gradient causes the network to converge very slowly due to small changes propagated to weights. Whereas an exploding gradient causes the network to possibly miss the optimal weight configuration due to large changes propagated to weights.
- Must have low computational cost.

Activation functions such as sigmoid and tanh result in a vanishing gradient, yet the following functions resolve that issue for both positive and negative vanishing gradients: leakyReLu, PReLu, ReLu6, SELU, Swish, hard-Swish and Mish. All aforementioned activation functions provide a transformed, continuous output and could be useful for the architecture of a CNN which involves lots of down and up sampling. Furthermore as tested by the authors, those activation functions work effectively for CNNs [6].

D. Layer Considerations

The pooling layer of the neural network ensures invariance to image transformations. If the image is rotated, translated or distorted, then the model becomes highly-sensitive to the noise and could perform ineffectively on validation sets. To counteract this effect, the added pooling layer down samples the image to reduce noisy behavior.

The dropout layer provides regularization to the neural network to prevent over-fitting. The parameters of other regularization methods include L1 and L2-regularization are computationally-expensive to tune. Therefore the dropout layer provides an efficient solution. It randomly selects a neuron to remove temporarily during training. The net effect is that the model learns a sparse representation of the input data rather than fitting to exact details. Hence the model can better generalize to unseen data [7].

III. Methods

A. Research Objectives

Research objectives for the study include:

1) Validation set accuracy by last epoch exceeds 90%
2) Model is at least less than 5MB in size, but ideally as small as possible
3) Model can be saved into file for easy use in embedded application
4) Model's F-1 score exceeds 0.9 to ensure no false positives or negatives

Referencing the validation set to bench-mark the model is necessary to check that the model is not over-fitting to training data. Furthermore, sizing requirements are put in place and later justified to ensure the model is small enough for use in an embedded application. Finally, the F-1 score is essential as another performance measure to ensure that the model is not mis-classifying images often.

B. Research Methodology

Test the hypothesis: smaller machine learning models can perform simple image classification tasks effectively. Here 'simple image classification' implies that the image contains just one subject. Furthermore, 'smaller' refers to memory size of the models themselves and any model less than 5MB in size is considered small enough.

As mentioned earlier, memory size can be reduced by methods such as quantization. But for experimental completeness and to compare models, this study computes model size by the number of trainable parameters. Obviously more parameters will increase the memory size of a model, even after compression methods are applied, hence it is a fair metric for sizing models. The selected threshold is based on the memory requirements in an embedded system, and on the size of the MobileNetV2 architecture which comes is the smallest pre-trained model coming in at a size of 14MB [2].

The experiment uses Keras for implementing and testing the models, which is built on top of TensorFlow. TensorFlow uses 32-bit floating-point numbers to perform computations with, called the float32 data-type. Knowing this and the number of parameters stored in each model makes computing the model size in bytes a simple product between model parameters and the data-type size.

$$S(m) = 4(n(m)) \tag{1}$$

S(m) represents the size of a model m in bytes, n(m) represents the number of trainable parameters of the model and 4 indicates that each parameter is 4 bytes in memory.

Models that satisfied the requirements of being small and able to perform a simple image classification task include:

- Logistic Regression model
- Vanilla CNN model
- Modified CNN model

The vanilla CNN only contains convolutional and fully-connected layers, furthermore it applies the commonly-used ReLu activation function. The modified CNN contains additional pooling and drop-out layers such that the model can learn a sparse representation of the data, be less prone to image transformations, and learn effectively with less parameters due to greater down-sampling. Additionally, the modified CNN architecture employs the use of a LeakyReLu activation function to allow better gradient flow during back propagation and improve training. The logistic regression model is the simplest one and involves a sigmoid function to perform classification.

Fig. 1: MNIST Fashion Apparel Dataset

Apply the models to the MNIST clothing data set which consists of 60000 training and 10000 validation examples of 28 x 28 gray-scale (single-channel) images. The data set contains 10 classes of fashion apparel as displayed in Figure 1.

The classes cover: t-shirts, trousers, pullovers, dresses, coats, sandals, shirts, sneakers, bags, and boots respectively. Chose this data set due to its ease of setup as it is available as one of TensorFlow's built-in data sets, and it is sufficiently large.

C. F-1 Score Functionality

The F-1 score provides the most reliable measure of a model's classification accuracy, and it allows multiple models to be compared even if they work differently. Hence the F-1 score is a great metric to benchmark neural networks against other machine learning models, in this case logistic regression. Therefore understanding the F-1 score's functionality is imperative to see why it is well-suited to classification tasks.

The F-1 score combines two other metrics together named: precision and recall. Precision is a measure of the model's false positive rate and recall is a measure of the model's false negative rate. False positives occur when the model classifies an input as belonging to class A, when really it could belong to some other class B. Conversely, false negatives occur when the model classifies an input as not belonging to class A, when really it does. A higher precision and recall score indicate lower false positive and negative rates respectively. False positives and negatives typically apply to binary classification problems, but can be generalized to multi-class classification problems by considering whether an input is mapped to the right class or not. Given that the F-1 score is a combination of precision and recall, and precision and recall measure the ratio of correctly classified samples, then higher the F-1 score is, the more samples are correctly classified.

$$F1(b) = \frac{2P(b)R(b)}{P(b) + R(b)} \tag{2}$$

F-1 score equation 2 where R(b) refers to the recall for class b and P(b) refers to the precision for class b.

$$R(b) = \frac{TP(b)}{TP(b) + FN(b)} \tag{3}$$

Recall equation 3 where TP(b) refers to all true-positives for class b and FN(b) refers to all false-negatives for class b.

$$P(b) = \frac{TP(b)}{TP(b) + FP(b)} \tag{4}$$

Precision equation 4 where TP(b) refers to all true-positives for class b and FP(b) refers to all false-positives for class b.

Evidently, the F-1 score computation for a multi-class problem does not change, as it is in terms of a single class only. Hence can apply the formula individually across each class to determine the effective classification rate of every model [8].

D. Model Architectures

Model architectures for both neural networks to be tested are shown below. Evidently based on the parameters of each model, the modified CNN is approximately $\frac{1}{4}$ the size of the vanilla CNN.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
conv2d_1 (Conv2D)	(None, 24, 24, 64)	18496
conv2d_2 (Conv2D)	(None, 22, 22, 128)	73856
conv2d_3 (Conv2D)	(None, 20, 20, 64)	73792
conv2d_4 (Conv2D)	(None, 18, 18, 32)	18464
flatten (Flatten)	(None, 10368)	0
dense (Dense)	(None, 64)	663616
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 10)	330

Total params: 850,954
Trainable params: 850,954
Non-trainable params: 0

(a) Vanilla CNN

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_6 (Conv2D)	(None, 11, 11, 64)	18496
conv2d_7 (Conv2D)	(None, 9, 9, 128)	73856
conv2d_8 (Conv2D)	(None, 7, 7, 64)	73792
conv2d_9 (Conv2D)	(None, 5, 5, 32)	18464
flatten_1 (Flatten)	(None, 800)	0
dense_3 (Dense)	(None, 128)	102528
dense_4 (Dense)	(None, 64)	8256
dense_5 (Dense)	(None, 32)	2080
dropout (Dropout)	(None, 32)	0
dense_6 (Dense)	(None, 10)	330

Total params: 298,122
Trainable params: 298,122
Non-trainable params: 0

(b) Modified CNN

Fig. 2: CNN Architectures and Parameters

E. Hyper-parameter Tuning

An appropriate value for the alpha hyperparameter must be determined to use in the LeakyReLu activation function for training the modified CNN. The model is tuned on the entire training and validation sets to check which alpha value works best in the general case. Discovered that as the alpha value increases, performance drops off hence we decided to go with a smaller alpha value of 0.2, as indicated in figure 2.

For the logistic regression model the hyperparameters explored were: solver, penalty and the C-value. The solver value represents the algorithm to be used in the optimization, penalty refers to the regularization penalty and the C-value is the inverse of the regularization strength (high c-value gives more

weight to training data and less to the regularization value). The repeated stratified K-fold technique was used, providing 5 splits of the data and 5 iterations during the grid search. K-folds aid in reducing sample bias and stratified samples are ones that preserve the class representation in the data set. Each hyperparameter was tuned one at a time, on only 10% of the total data set to help reduce execution time. The following selections were made for the hyperparameters: saga(solver), l2(penalty), 0.1(C-value).

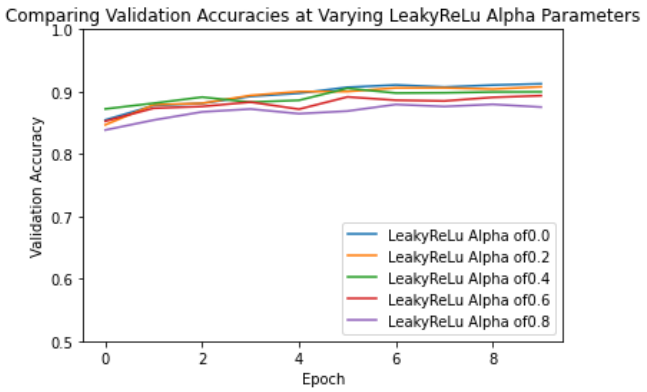


Fig. 3: Modified CNN Activation Function Tuning

IV. Experimental Results

Results obtained after training the models on test and validation sets are summarized. In figure 4, the F-1 scores are compared to determine how many false negatives and positives the models produced. Furthermore, exact model sizes are shown in figure 5. In figure 6, training and validation set accuracy of all three models is plotted across every epoch of the CNNs to see that the models do follow a pattern, converge, and do not over-fit to the data set. Furthermore in figure 6, the validation accuracy in the final epoch is compared against model size to determine which model maintains effective performs at the smallest size possible as per earlier mentioned research objectives. Computation for model size was based on equation 1, where the number of parameters in each CNN come from the architecture diagrams shown in figure 2. Normalized confusion matrices used to show the true-positive classification rate across every class are shown in figure 7 for each model.

F-1 Score Comparison Across Models		
Vanilla CNN	Modified CNN	Logistic Regression
0.90567	0.90526	0.84517

Fig. 4: F-1 score Comparison

V. Discussion

Logistic Regression trailed the two CNN models but produced acceptable classification accuracy and F1 score while having the lowest model size. The model's hyperparameter tuning proved to be very resource intensive, as such optimization was sacrificed for speed. For one, taking the same subset of the total data during tuning introduces a training bias when optimizing for the hyperparameters. This might explain why the training accuracy is slightly higher than the validation accuracy. Second, tuning one hyperparameter at a time misses potential synergistic combinations that could bring forth better model performance. Covering more hyperparameter combinations could help improve the F1 score of the logistic regression model.

Size Comparison Across Models (MB)		
Vanilla CNN	Modified CNN	Logistic Regression
3.24	1.13	0.03

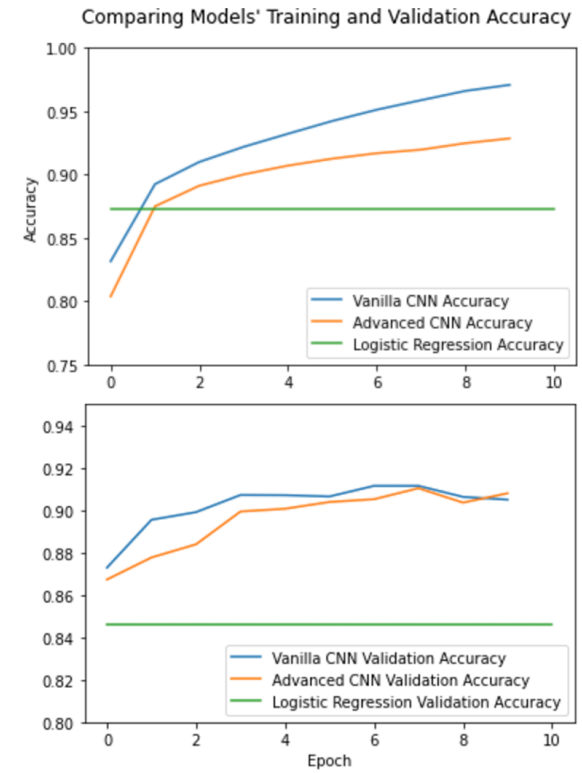
Fig. 5: Size Comparison Computed as per Equation 1

The performance of the vanilla CNN and modified CNN remained similar, both in terms of their validation accuracies and F-1 scores. The results demonstrate that even with less parameters, performance was maintained for a simple image classification task. In particular, the high F-1 score is especially great since it means that the model correctly classifies images most of the time. Furthermore, the high validation accuracy scores are promising because it means that the models do not over fit to the training set. With the use of pooling and drop-out layers of the modified CNN, it should have learned a transform-invariant, sparse representation of the data set hence it should work better for more abstract, complex images.

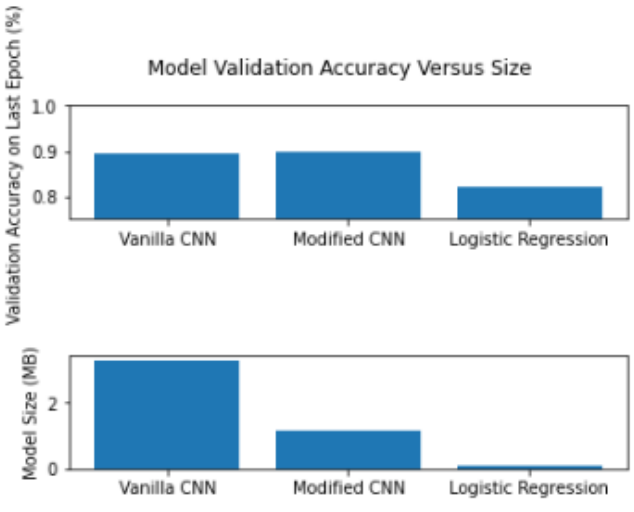
The confusion matrices provide a better understanding of the classification rate for each class in every model It is evident from these matrices that both CNN models and the logistic regression model suffered when it came to classifying image examples from class 6 which includes images of shirts as per figure 8. Looking at the shirts there are a lot of similarities between it and classes 0, 2 and 4 (T-shirt, pullover and coat). We can see this in figure 9, where the model is only around 50% confident in correctly classifying a class 6 image and is 28%, 10% and 10% confident in classifying classes 0, 2 and 4 respectively.

It would be reasonable to assume if class 6 is not well distinguished from classes 0, 2 and 4 then the reverse should also be true. However it is interesting to see that this misclassification seems to uniquely affect class 6 images. This could be attributed to a large variation of shirt styles that can't be well captured by the model. Potentially class 6 images might need to be broken down into further classes, or more detailed images are needed to help train the model to better distinguish images from class 6. This would come at the cost of a more complex model and could diminish the performance of the model or increase training time.

Overall the modified CNN maintains a validation accuracy of approximately 90% with an F-1 score of 0.905 all while maintaining a size of 1.13MB. These results are encouraging in regards to the feasibility of smaller models being effectively



(a) Training and Validation Performance



(b) Size Versus Accuracy Comparison

Fig. 6: Model Performance Comparison

used for simple classification tasks in resource-limited systems. However further work must be done to validate results for more complex image data sets.

VI. Conclusions and Future Work

Either a Vanilla CNN or a more advanced CNN with dropout and pooling layers work effectively to perform image classification on small, simple images. Using dropout and pooling layers down-sample images greatly and simplify model parameters to achieve massive reductions in memory usage, which is crucial for resource-intensive applications. Therefore it is reasonable to conclude simpler deep-learning models can be built in-house for embedded devices rather than using pre-trained off-the-shelve networks such as VGG-19, but do require more work to better optimize them for those use cases. It is also relevant to note that the much smaller size of the logistic regression model in comparison to the CNNs could justify research into optimizations for extremely resource-limited applications where less-general classifications are necessary whereas the CNNs are likely better solutions for more general classification problems.

For the future, additional work can be done using more complex data sets of higher resolution images to check if simple models can still be used as an alternative to pre-trained very deep neural networks. This would be a good test for understanding the model's performance on real world data which is an essential step in considering the feasibility of these models in embedded systems.

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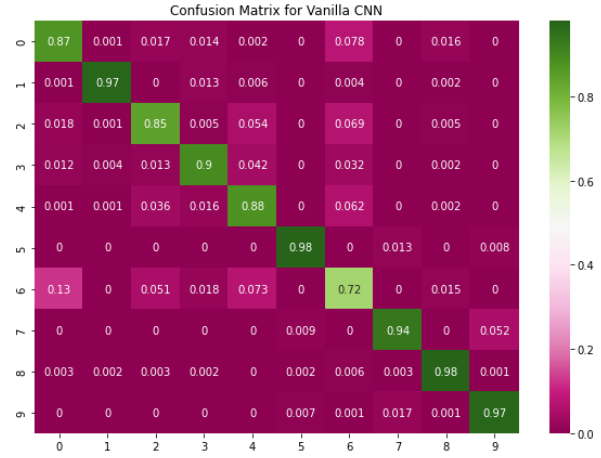
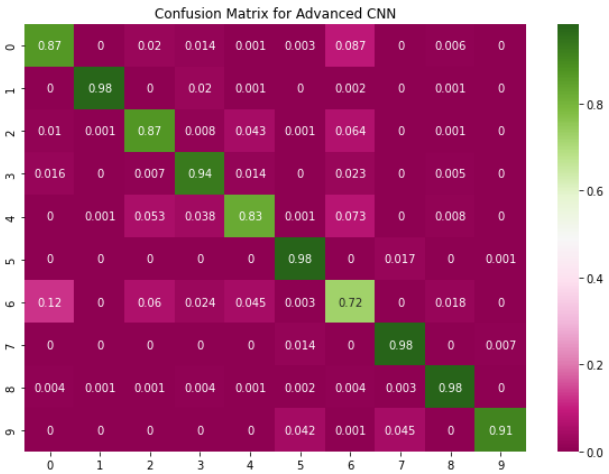
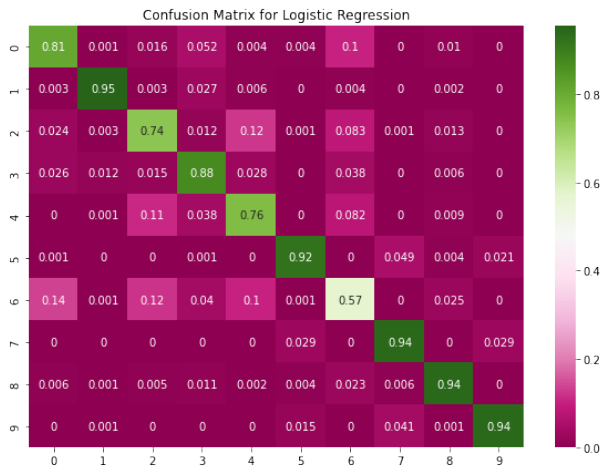


(a) Vanilla CNN Confusion Matrix



(b) Modified CNN Confusion Matrix

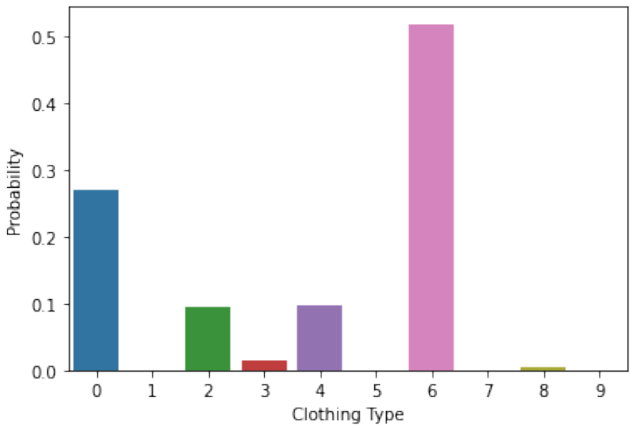


(c) Logistic Regression Confusion Matrix

Fig. 7: Analyzing Classification Results By Class

Fig. 8: MNIST Class 6 (Shirts) [9]

(a) [Select Class 6 Image (Shirt



(b) [Conditional Probability for Model's Prediction per Class

Fig. 9: Model's class 6 classification performance