

# Image Classification using Convolutional Neural Networks

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## 1 Introduction

This report shows the process of developing and evaluating convolutional neural network models for image classification tasks using the CIFAR-10 dataset. The goal is to train multiple neural network architectures, experiment with various hyperparameters, and get better than 0.75 accuracy.

## 2 Data Understanding

The CIFAR-10 dataset contains 60,000 small 32x32 pixel color images grouped into 10 distinct classes (e.g., airplanes, cars, birds). The data is split into 50,000 training images and 10,000 test images, with each class having exactly 6,000 images total. Classes are mutually exclusive—for example, “automobile” (cars) and “truck” (large trucks) are strictly separated.

Key observations:

- Images are low-resolution, which may limit fine details.
- The dataset is balanced, with equal representation across classes.
- Training data is divided into five batches, but each class retains 5,000 training images overall.

## 3 Data Preparation

Using the starter code file `open_data.py` we made sure to separate the training from the testing and inside the training we also separated 10,000 images from the training data as validation data for the models to have a better idea of how the model predicts without showing it the testing data.

## 4 Model Architectures

(You can see the information that the model spits out on my `progress.md` file in the code)

The following models were trained:

## 4.1 Model A

This was only a test model, not even trained with the CIFAR-10 data but with the Fashion MNIST dataset. This was to make sure that the starter code worked from the begginin so that I could change it to the CIFAR-10 dataset after. The optimizer is Adam(learning\_rate=0.0001)

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 64)	3,200
max_pooling2d (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_1 (Conv2D)	(None, 14, 14, 128)	73,856
conv2d_2 (Conv2D)	(None, 14, 14, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 64)	401,472
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 10)	650

### Training Results:

- Training Accuracy: 0.8587
- Validation Accuracy: 0.8690
- Validation Set Accuracy: 0.86

### Confusion Matrix:

741	4	18	49	8	0	183	0	6	0
1	996	4	12	1	0	5	0	0	0
8	1	838	10	82	0	41	0	0	0
13	28	12	860	37	0	30	0	2	0
2	3	161	63	691	0	73	0	0	0
0	0	0	0	0	981	0	28	3	5
81	7	164	32	87	0	615	0	10	0
0	0	0	0	0	37	0	934	3	23
3	0	8	6	10	5	9	0	948	1
0	0	0	1	0	13	0	47	0	956

**Learning Curves:** There are multiple learning curves because I used the `cnn.bash` that was in the starter code to train it so what it would do is grab the first 10,000 data and train and then the next batch and retrain and so on until the validation batch (that gave us the confusion matrix).

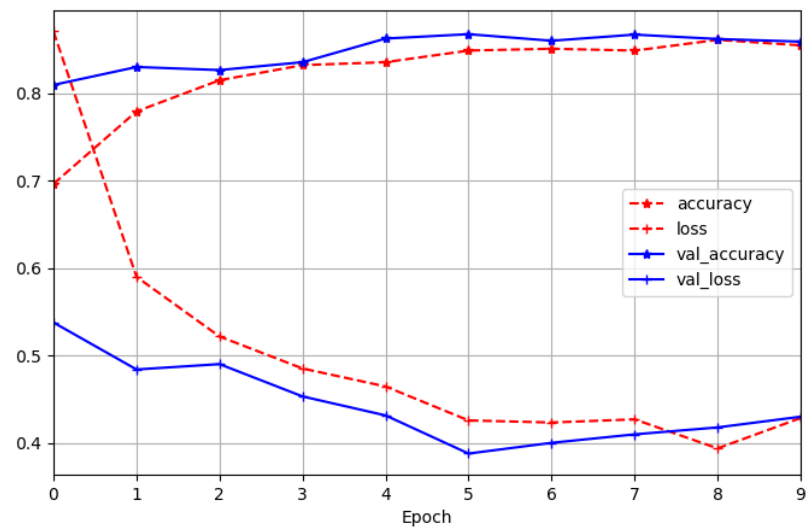


Figure 1: Learning Curve for Model A. First training.

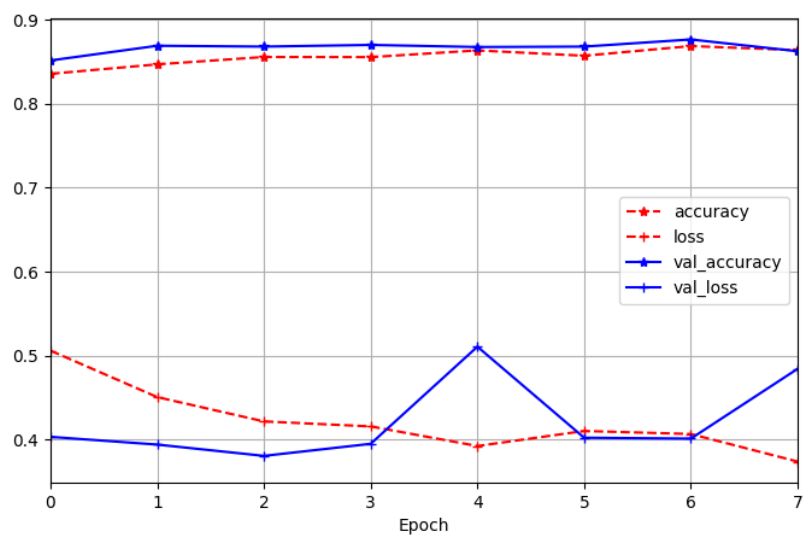


Figure 2: Learning Curve for Model A. Second training.

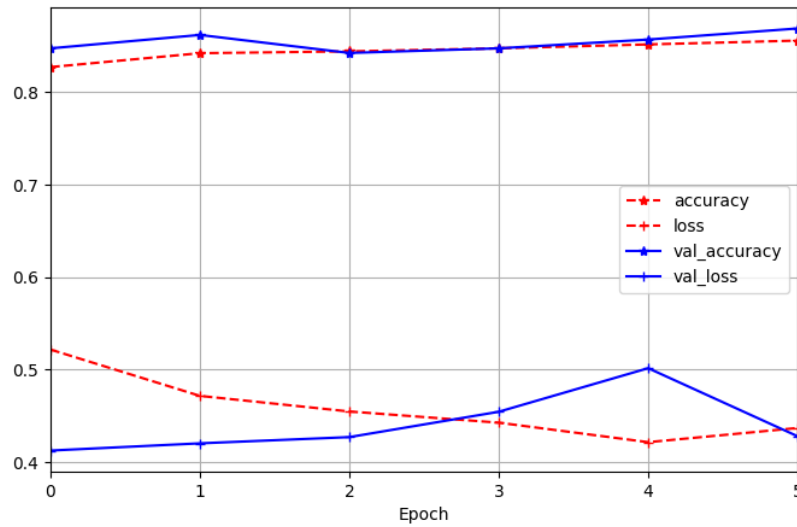


Figure 3: Learning Curve for Model A. Third training.

This model took around 15 minutes to train on all the batches and the accuracy was really good for the first try. However, as I mentioned before, this is just a test model on the Fasion MNIST to make sure everything works and take a look at how a good training epoch looks like and the graphs.

## 4.2 Model B

For this model I didn't change anything but the dataset from Fasion to CIFAR-10. I kept the same layer format as the last model to see how it would do with this dataset. The optimizer is Adam(learning\_rate=0.0001)

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 64)	9,472
max_pooling2d (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_1 (Conv2D)	(None, 14, 14, 128)	73,856
conv2d_2 (Conv2D)	(None, 14, 14, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 64)	524,352
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 10)	650

### Training Results:

- Training Accuracy: 0.8197
- Validation Accuracy: 0.6495
- Validation Set Accuracy: 0.66

### Confusion Matrix:

769	20	28	22	13	9	5	12	81	51
36	787	1	8	5	1	9	2	32	108
124	9	436	84	139	75	63	34	16	13
24	9	48	492	83	174	58	37	13	29
45	2	68	83	659	26	30	74	14	10
9	3	52	235	62	546	23	58	7	9
7	11	42	109	84	24	711	13	13	19
32	1	17	56	106	78	2	726	2	26
107	26	4	21	4	4	5	8	801	24
38	125	1	21	4	9	8	12	27	698

**Learning Curves:** There are multiple learning curves because I kept the `cnn.bash` format of training on the first batch and then the next one and so forth, but since the new dataset has 50,000 training images and we use 40,000 to train it generated a learning curve per training session.

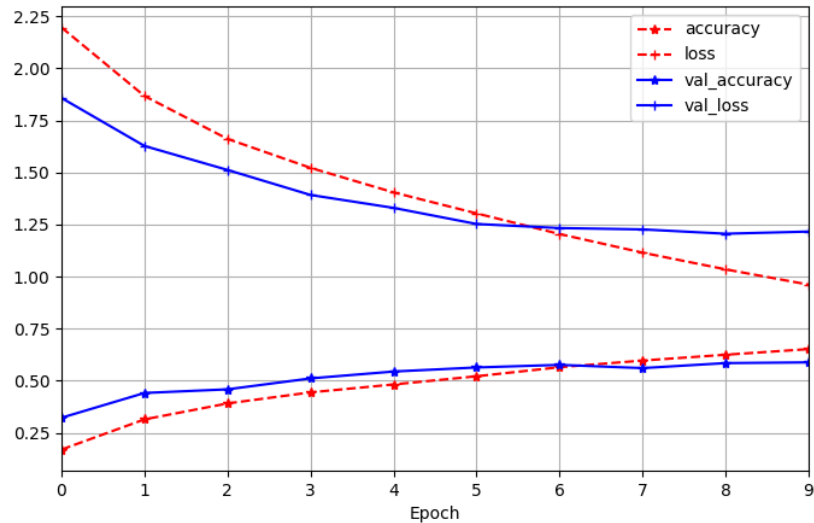


Figure 4: Learning Curve for Model B. First training.

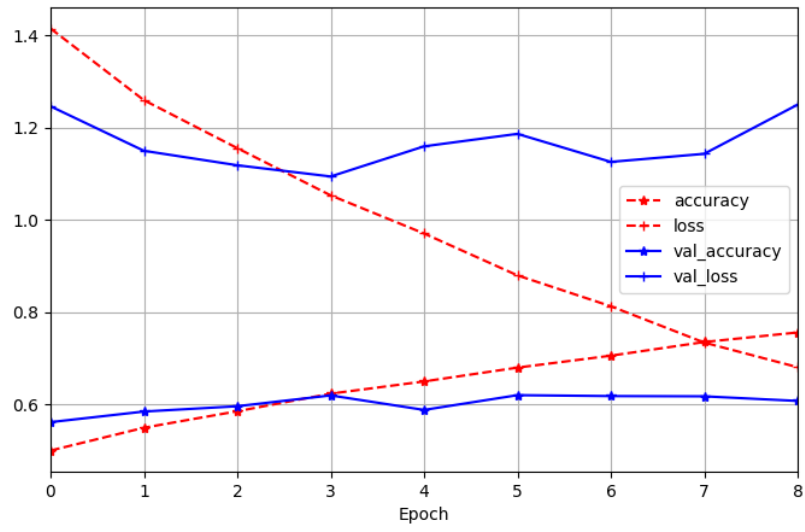


Figure 5: Learning Curve for Model B. Second training.

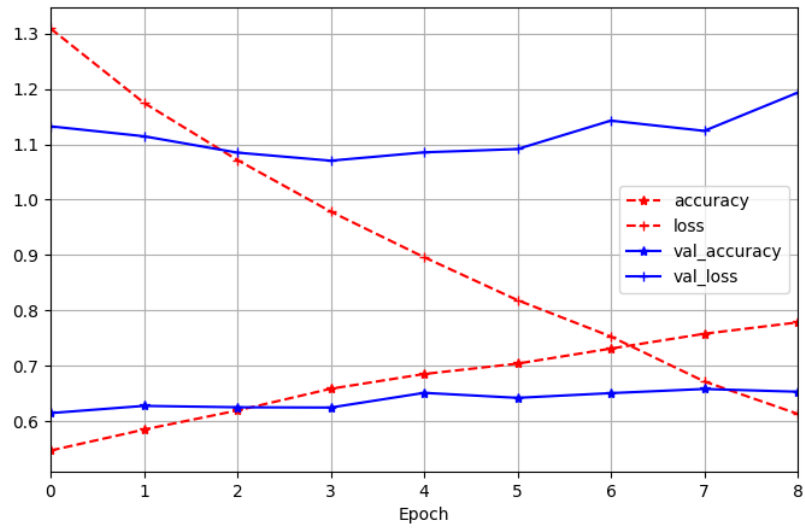


Figure 6: Learning Curve for Model B. Third training.

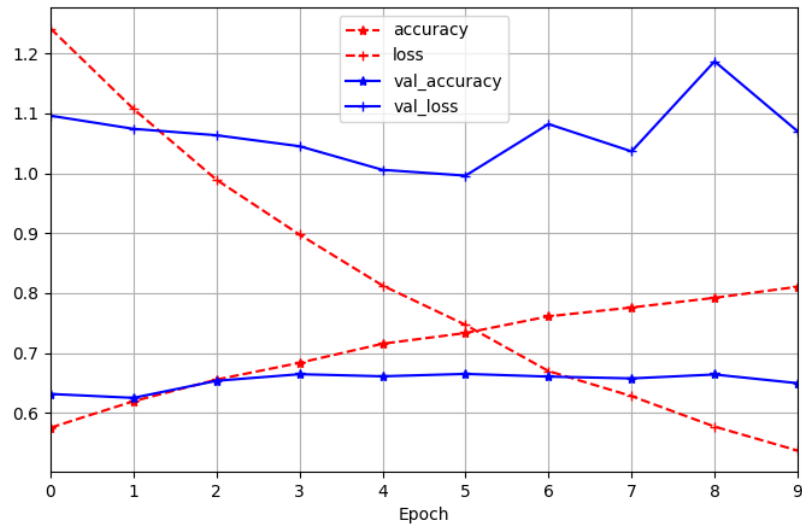


Figure 7: Learning Curve for Model B. Third training.

This model took about 30 minutes. I can see that this model was not good at generalizing and it was overfitting because towards the end the difference in between the accuracy and the validation accuracy was big (0.8197 vs 0.6495). I also realized that in the first training batch it was doing good but it stopped because I had a maximum of 10 epochs so that is something I will look into in the next models. Not great but not a bad start.

### 4.3 Model C

I figured out from last model that the batch size was 1 and that was slowing down the process so I changed it to 32. The optimizer is Adam(learning\_rate=0.0001) For the structure of the model I followed the simplest in-class recommendation:

- Conv (bigger kernel size)  
Bigger kernel size to capture large scale info before pooling.
- Pooling  
-----
- Conv (smaller kernel size)
- Conv (smaller kernel size)  
Now we want to pay more attention to small collections of things  
so thats why smaller kernel size.
- Pooling  
-----
- ^ as many as wanted  
-----
- Flatten
- Dense  
-----
- ^ as many as wanted
- Output

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 64)	9,472
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 128)	204,928
conv2d_2 (Conv2D)	(None, 16, 16, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 256)	0
flatten (Flatten)	(None, 4096)	0
dense (Dense)	(None, 128)	524,416
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1,290



### Training Results:

- Training Accuracy: 0.8036
- Validation Accuracy: 0.6620
- Validation Set Accuracy: 0.66

### Confusion Matrix:

754	30	53	6	22	8	18	20	69	30
41	818	6	6	4	2	15	4	17	76
87	9	563	54	95	42	72	37	19	15
31	11	90	436	76	145	94	41	11	32
36	7	117	52	596	26	57	108	8	4
7	6	101	220	59	476	45	76	7	7
10	14	53	52	66	11	793	9	8	17
18	4	46	39	91	51	5	778	1	13
105	66	15	18	13	2	11	3	746	25
46	155	11	9	4	9	15	30	28	636

### Learning Curves:

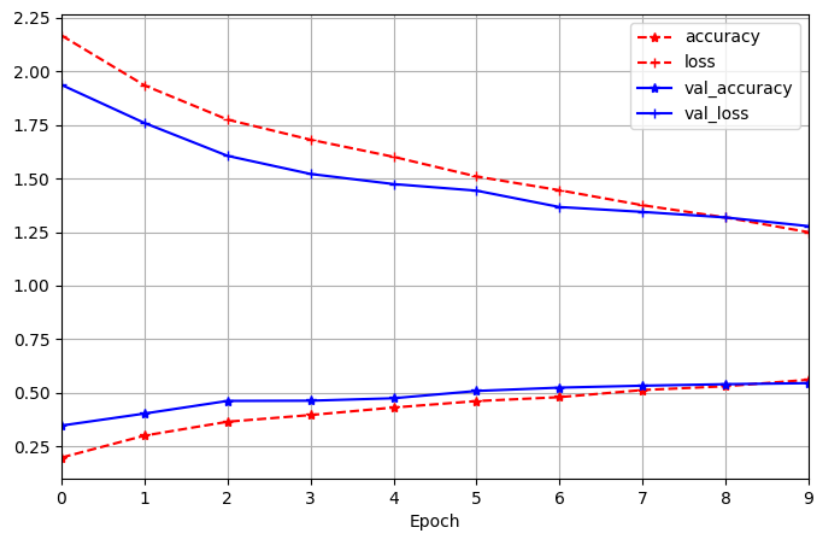


Figure 8: Learning Curve for Model C. First training.

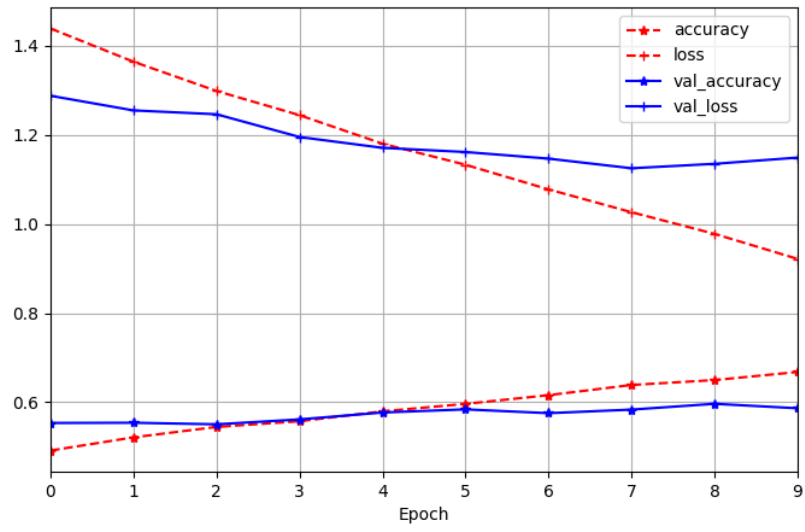


Figure 9: Learning Curve for Model C. Second training.

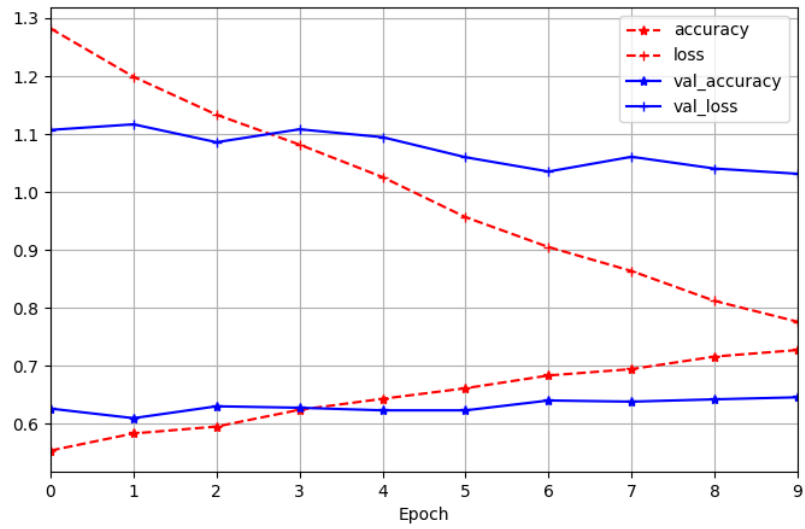


Figure 10: Learning Curve for Model C. Third training.

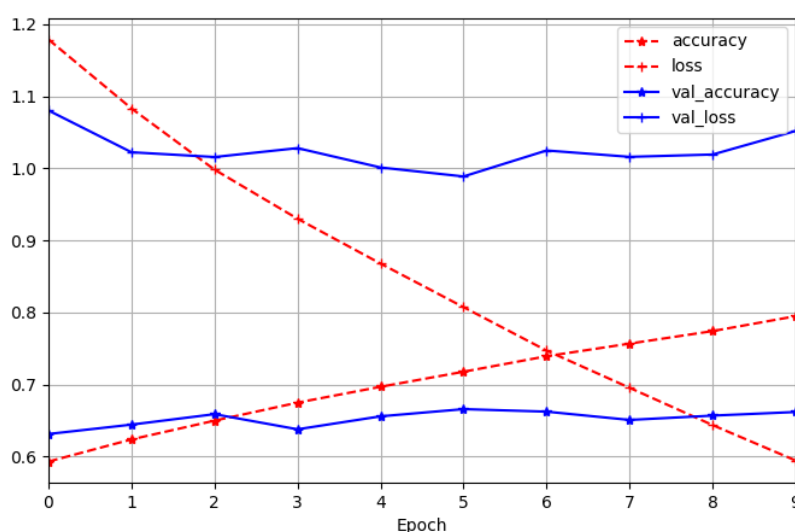


Figure 11: Learning Curve for Model C. Third training.

With the new batch size this took 20 minutes. However, my computer was boiling and it does not have fans (See picture bellow) so I decided to try and install the GPU part of Tensorflow so that it can use my mac's GPU and hope that that will make it faster and not as hot. I hadn't changed the epochs from 10 and I can still see in the first training that it would've gone for longer. The accuracy is about the same so I need to change something more.

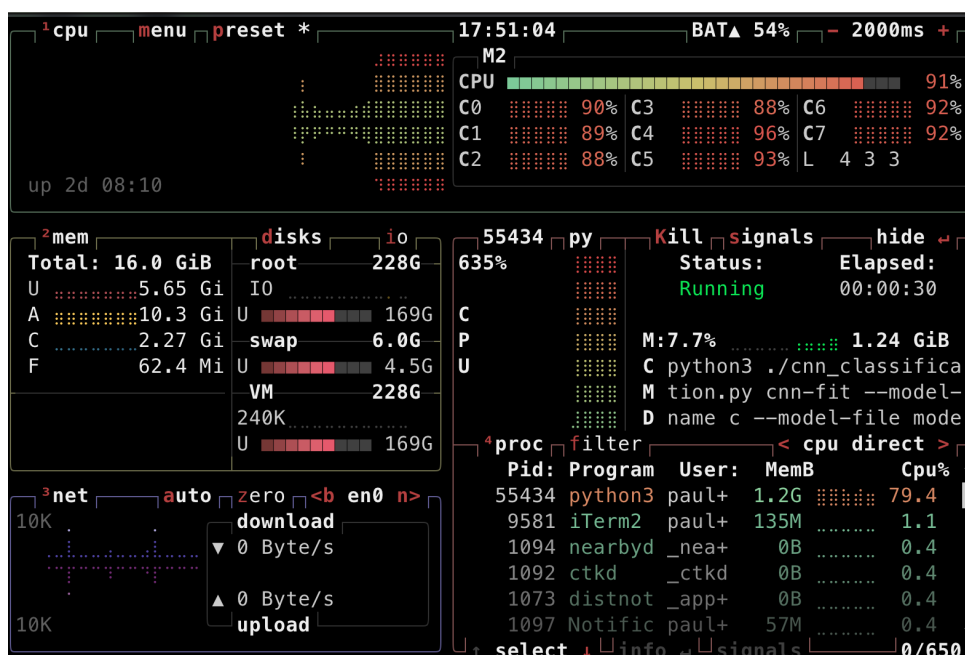


Figure 12: CPU usage with btop

## 4.4 Model D

For this model's structure I took out the additional convolutional and pooling layers for more to see if they were important. I also figured out the GPU with TensorFlow The optimizer is Adam(learning\_rate=0.0001)

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 64)	9,472
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 128)	204,928
conv2d_2 (Conv2D)	(None, 16, 16, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 128)	1,048,704
dense_1 (Dense)	(None, 128)	16,512
dropout (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 10)	1,290

### Training Results:

- Training Accuracy: 0.2587
- Validation Accuracy: 0.4170
- Validation Set Accuracy: 0.34

### Confusion Matrix:

406	26	43	5	14	18	71	130	131	166
22	166	2	5	2	6	112	65	26	583
93	4	77	7	53	68	399	198	29	65
16	4	28	23	5	155	390	245	8	93
36	3	40	5	53	30	515	266	14	49
9	1	23	20	5	259	377	254	3	53
6	7	19	1	10	17	772	129	8	64
21	11	8	10	9	43	220	621	6	97
189	33	26	14	3	35	57	39	321	287
21	21	2	6	2	9	69	73	11	729

### Learning Curves:

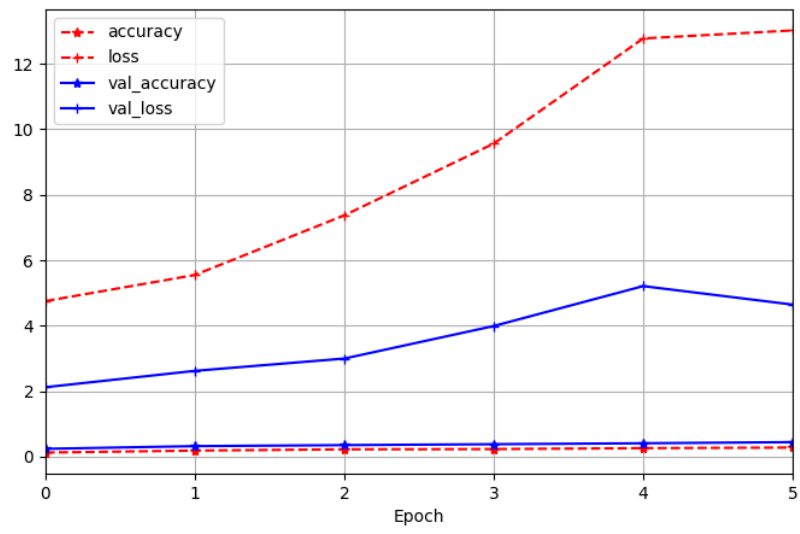


Figure 13: Learning Curve for Model D. First training.

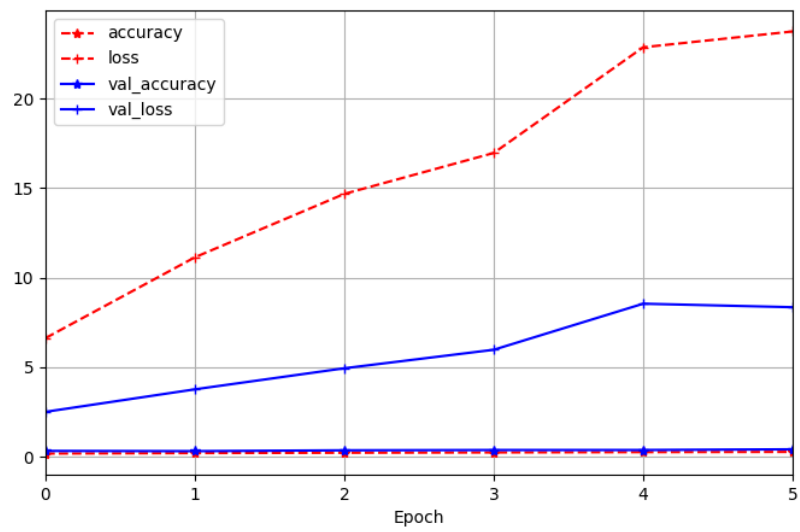


Figure 14: Learning Curve for Model D. Second training.

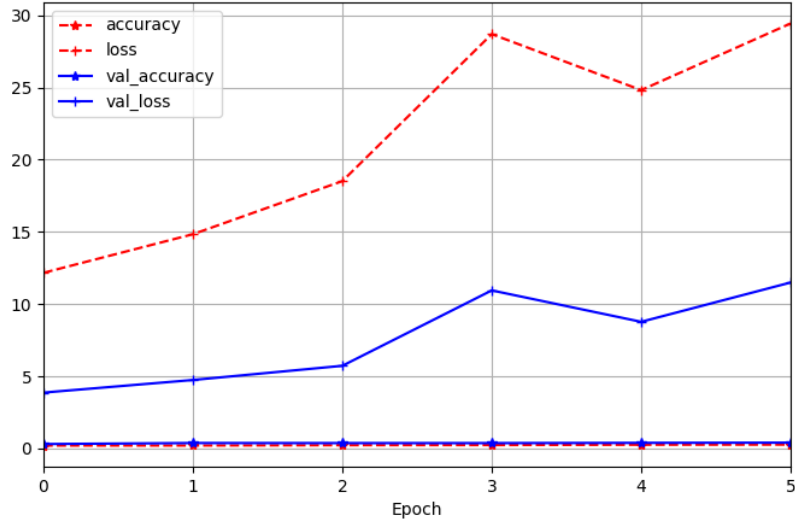


Figure 15: Learning Curve for Model D. Third training.

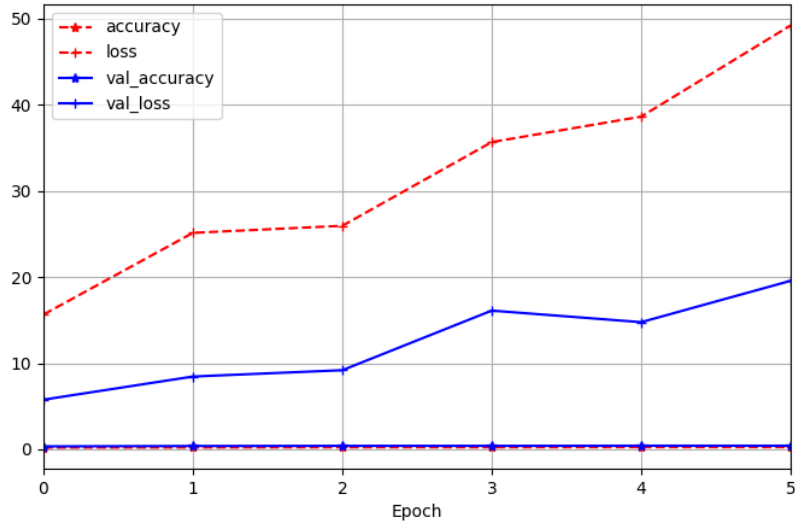


Figure 16: Learning Curve for Model D. Third training.

This one took about 6 minutes to finish training. I am glad I now have the GPU available because I would've been disappointing to wait all the time and heat for such a bad model. Now I know that the recommended structure is recommended for a reason and I will stick to it.

## 4.5 Model E

For this model I moved into training with all the data all at once instead of the different batches. I also changed the batch size to 16 and I added more dropout layers with smaller rates (0.25 or 0.15 instead of 0.5), I also added one conv and one pooling more and I changed the optimizer to `Adamax(learning_rate=0.001, weight_decay=1e-4)`. I also trained with 20 epochs to make sure it could converge.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 64)	9,472
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 128)	204,928
conv2d_2 (Conv2D)	(None, 16, 16, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
dropout (Dropout)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 256)	0
conv2d_4 (Conv2D)	(None, 4, 4, 256)	590,080
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 256)	0
dropout_1 (Dropout)	(None, 2, 2, 256)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 128)	131,200
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1,290

### Training Results:

- Training Accuracy: 0.7707
- Validation Accuracy: 0.7402
- Validation Set Accuracy: 0.73

### Confusion Matrix:

744	14	70	18	22	10	8	10	62	52
16	796	6	7	7	4	9	4	15	125
59	2	685	56	73	42	41	12	11	12
17	2	91	540	55	163	56	19	1	23
24	1	131	66	666	38	26	45	5	9
3	0	96	177	45	617	24	35	1	6
4	2	78	81	38	32	786	4	4	4
10	0	61	55	77	60	3	765	2	13

45	32	16	22	9	7	8	6	830	29
11	41	10	18	2	9	6	4	17	825

**Learning Curve:** Since I only trained once with all the data we only got one learning curve.

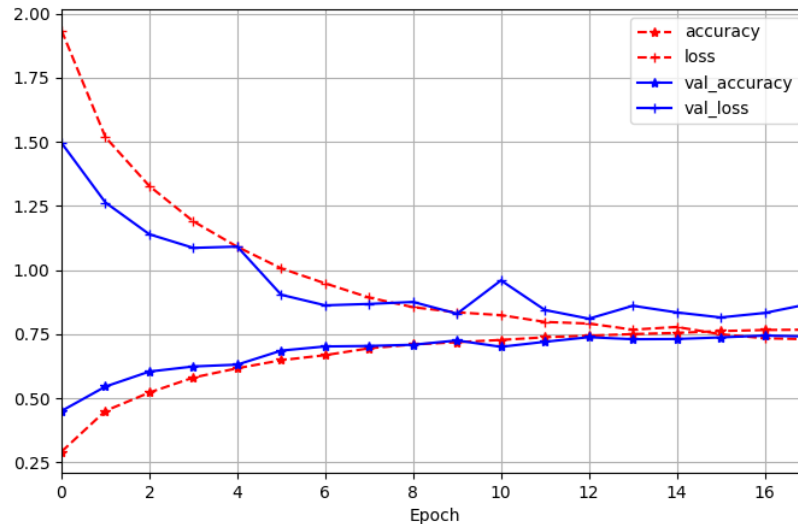


Figure 17: Learning Curve for Model E. First training.

This model took about 20 minutes to finish

## 4.6 Model F

I kept the same optimizer `Adamax(learning_rate=0.001, weight_decay=1e-4)` and I also remembered from last assignments to use batch normalization and activation layers so I added those all over to see if the model would generalize better. I also found `spatial_dropout2d` by asking chatgpt how to make my model better with keras, it sounded interesting so I added it.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 64)	4,864
batch_normalization (BatchNormalization)	(None, 32, 32, 64)	256
activation (Activation)	(None, 32, 32, 64)	0
max_pooling2d (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_1 (Conv2D)	(None, 16, 16, 128)	204,928
batch_normalization_1 (BatchNormalization)	(None, 16, 16, 128)	512



+-----+-----+-----+		
activation_1 (Activation)	(None, 16, 16, 128)	0
+-----+-----+-----+		
conv2d_2 (Conv2D)	(None, 16, 16, 128)	147,584
+-----+-----+-----+		
batch_normalization_2	(None, 16, 16, 128)	512
(BatchNormalization)		
+-----+-----+-----+		
activation_2 (Activation)	(None, 16, 16, 128)	0
+-----+-----+-----+		
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
+-----+-----+-----+		
spatial_dropout2d (SpatialDropout2D)	(None, 8, 8, 128)	0
+-----+-----+-----+		
conv2d_3 (Conv2D)	(None, 8, 8, 256)	295,168
+-----+-----+-----+		
batch_normalization_3	(None, 8, 8, 256)	1,024
(BatchNormalization)		
+-----+-----+-----+		
activation_3 (Activation)	(None, 8, 8, 256)	0
+-----+-----+-----+		
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 256)	0
+-----+-----+-----+		
flatten (Flatten)	(None, 4096)	0
+-----+-----+-----+		
dense (Dense)	(None, 256)	1,048,832
+-----+-----+-----+		
batch_normalization_4	(None, 256)	1,024
(BatchNormalization)		
+-----+-----+-----+		
activation_4 (Activation)	(None, 256)	0
+-----+-----+-----+		
dropout (Dropout)	(None, 256)	0
+-----+-----+-----+		
dense_1 (Dense)	(None, 10)	2,570
+-----+-----+-----+		

### Training Results:

- Training Accuracy: 0.9138
- Validation Accuracy: 0.7979
- Validation Set Accuracy: 0.79

### Confusion Matrix:

+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+											
816	5	42	16	16	13	6	2	68	26		
21	860	4	8	1	2	7	1	15	70		
47	4	691	54	65	51	45	15	12	9		
21	2	38	594	50	162	53	20	10	17		
20	1	48	67	774	34	17	40	7	3		

	7		2		37		147		32		719		15		35		4		6	
	11		3		36		54		25		17		876		2		5		4	
	9		1		23		56		50		63		3		825		4		12	
	30		16		10		9		3		6		10		2		905		13	
	24		46		3		4		5		7		6		1		31		816	
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+																				

Since this is my best model I am going to predict on the testing data and see if I actually get somewhat close to the validation Set Accuracy: **Testing Confusion Matrix:**

+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+																				
	820		11		50		16		9		5		10		6		48		25	
	16		871		2		5		1		3		6		0		22		74	
	47		2		674		60		70		54		47		27		9		10	
	18		3		46		606		59		166		43		27		16		16	
	18		2		48		52		780		30		29		29		10		2	
	12		0		22		145		42		715		18		35		2		9	
	6		3		24		51		26		25		855		1		4		5	
	8		1		24		34		44		59		4		808		6		12	
	47		12		10		11		6		9		5		3		884		13	
	39		49		7		4		4		6		3		4		32		852	
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+																				

	precision	recall	f1-score	support
0	0.80	0.82	0.81	1000
1	0.91	0.87	0.89	1000
2	0.74	0.67	0.71	1000
3	0.62	0.61	0.61	1000
4	0.75	0.78	0.76	1000
5	0.67	0.71	0.69	1000
6	0.84	0.85	0.85	1000
7	0.86	0.81	0.83	1000
8	0.86	0.88	0.87	1000
9	0.84	0.85	0.84	1000
accuracy			0.79	10000
macro avg	0.79	0.79	0.79	10000
weighted avg	0.79	0.79	0.79	10000

## 5 Model Comparison

Table 1: Comparison of CNN Models (B-F) on CIFAR-10

Model	Training Acc.	Val. Acc.	Val. Set Acc.	Key Features
B	0.8197	0.6495	0.66	Same as A but on CIFAR-10, overfitting observed
C	0.8036	0.6620	0.66	Modified structure (3 Conv + 3 Pool + 1 Dense), batch size=32
D	0.2587	0.4170	0.34	Reduced layers (2 Conv + 2 Pool + 2 Dense), poor performance
E	0.7707	0.7402	0.73	Added dropout (0.25/0.15), more Conv/Pool layers, full data
F	<b>0.9138</b>	<b>0.7979</b>	<b>0.79</b>	Added BatchNorm, Spatial-Dropout, Activation layers, best generalization

## 6 Conclusions

The results prove that convolutional neural networks can achieve strong performance on the CIFAR-10 dataset, with my best model (Model F) reaching 79.7% validation accuracy and 79% test accuracy. Several key insights:

- **Architecture Matters:** The progression from Model B to F shows that proper layer configuration (multiple convolutional blocks with BatchNorm and dropout) significantly impacts performance. Model F’s inclusion of spatial dropout and batch normalization proved particularly effective at preventing overfitting while maintaining high accuracy.
- **Training Strategy:** Using the full dataset (Model E onward) rather than batched training improved results substantially. The Adamax optimizer with weight decay ( $1e^{-4}$ ) also showed better convergence than the initial Adam implementation.
- **Current Limitations:** While Model F performs well, there remains a noticeable gap between training (91.4%) and validation accuracy (79.8%), suggesting some persistent overfitting. The model also shows weaker performance on classes like "cat" and "dog", which are visually similar.

These results confirm that careful architecture design and regularization are crucial for computer vision tasks, and that there remains room for improvement beyond the 80% accuracy threshold.