

# Artificial Neural Network – Homework 1

## Font Classification Using Multiple Layer Perceptron

Ammar Abdurrauf - 170421930

### Introduction

Datasets of 7 alphabets (A, B, C, D, E, J, K) in three different fonts were given to train a model using multiple layer perceptron method. Before training the model, the dataset was given some noises by randomly changing some pixels to a random integer among -1, 0, and 1 representing black, grey, and white respectively. Various optimization algorithms were used to train the model. The learning rate and several activation functions were varied to observe and analyze the behavior of the trained model.

### Methods and Dataset

#### *Dataset*

The datasets contain matrices of 7 alphabets with three different fonts resulting a total of 21 images. The matrices define a 9 by 7 pixels consisting of -1 and 1, where -1 represents black and 1 represents white. The datasets were imported to the Google Colab as matrices. Figure 1 shows the dataset used in this work.

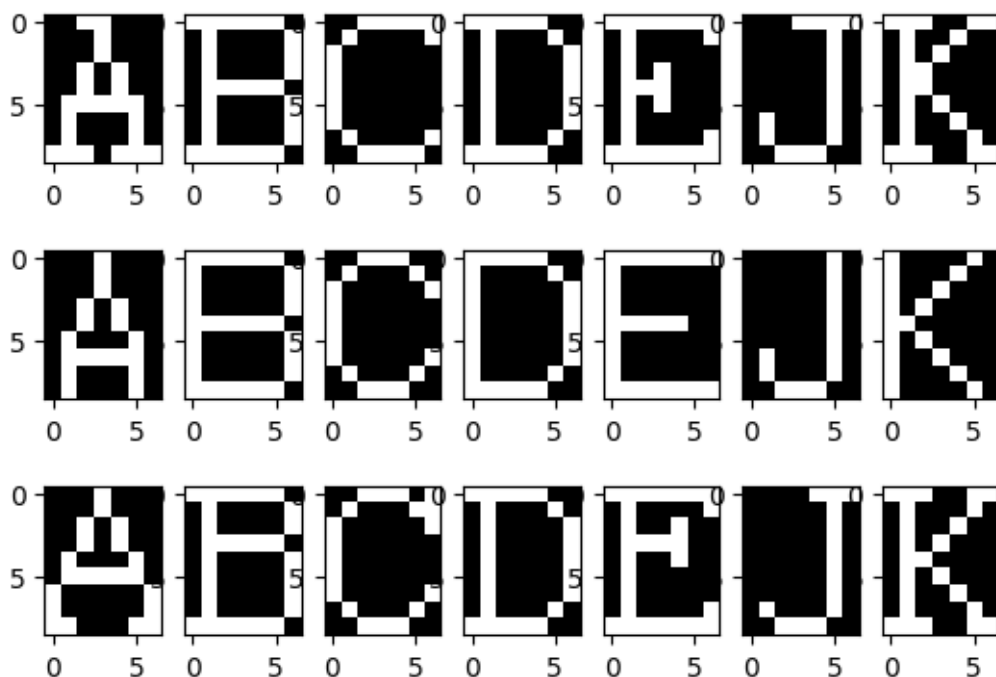


Figure 1. Datasets consist of different alphabets and fonts

#### *Adding Noise to The Dataset*

Two different approaches to add noises to the dataset were done. Firstly, 7 randomly selected pixels in a font were changed to a value among -1, 0, and 1 representing black, grey, and white respectively. The second approach also selects 7 random pixels in a font and changes those pixels

by reversing the value inside that pixel, this is done by multiplying the value within that pixel with -1. Finally, to obtain more datasets, 100 iterations for generating new fonts with noises were conducted for each font. Two new datasets each containing 2121 different alphabets were obtained (4242 in total). Datasets that added noise using the first and second approaches will be labeled as dataset #1 and dataset #2 respectively for convenience. The samples of font with noises can be seen in Figure 2 and 3.

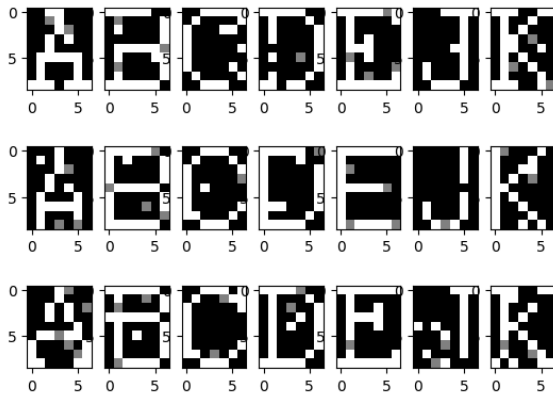


Figure 2. Font with noise #1

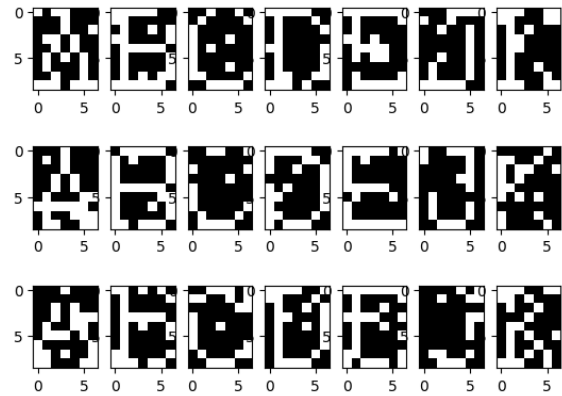


Figure 3. Font with noise #2

### *Variating The Optimizer Algorithm and Parameters*

The optimizer algorithms used to train the model were Adam (Adaptive Moment Estimation), RMSprop (Root Mean Square propagation), and SGD (Stochastic Gradient Descent) optimizers. The dense of the layers was kept to 9 by 7 input layers (63 in total), 10 layers with an activation function (will be variated in several trainings), and 7 output layers with softmax activation function. The variation of the optimizer, learning rate, and activation function used for training the model is shown in Table 1.

Training No	Optimizer	Learning Rate	Dataset #1	Dataset #2
			Activation Function on 2 <sup>nd</sup> layer	
1	Adam	0.001	Relu	Tanh
2		0.01	Sigmoid	Relu
3		0.2	Tanh	Sigmoid
4	RMSprop	0.001	Tanh	Sigmoid
5		0.01	Relu	Tanh
6		0.2	Sigmoid	Relu
7	SGD	0.001	Sigmoid	Relu
8		0.01	Tanh	Sigmoid
9		0.2	Relu	Tanh

Table 1. Variations of optimizer and parameters for the training

### **Results and Discussion**

The model training was conducted with 11 epoch and validation split of 0.2 for every datasets. The training resulted 18 models and history graphs during the training, such as accuracy, validation accuracy, loss, validation loss, and confusion matrix. The model's precision, recall, accuracy, and F1 scores are listed in Table 2.

Training No	Dataset #1 (%)				Dataset #2 (%)			
	Precision	Recall	F1	Accuracy	Precision	Recall	F1	Accuracy
1	99.84	99.84	99.84	99.84	99.68	99.68	99.68	99.69
2	100	100	100	100	99.53	99.52	99.52	99.53
3	95.19	94.30	94.29	94.34	95.12	93.97	93.67	94.03
4	100	100	100	100	99.68	99.68	99.68	99.69
5	100	100	100	100	99.68	99.68	99.68	99.69
6	99.84	99.84	99.84	99.84	46.25	56.83	48.37	57.23
7	99.53	99.53	99.53	99.53	98.59	98.59	98.58	98.58
8	100	100	100	100	99.53	99.52	99.52	99.53
9	78.37	85.40	80.68	85.53	99.22	99.21	99.21	99.21

Table 2. Model's precision, recall, F1, and accuracy scores

### ***Dataset #1***

Model training using Dataset #1 was conducted with several optimizer algorithms and variation of learning rate and activation function. As shown in Table 2, the model that used the RMSprop optimizer algorithm during training achieved the best results among the others. It reached 100% accuracy and F1 score when using a combination of the tanh and relu activation functions, along with learning rates of 0.001 and 0.01. Model training that uses learning rate of 0.01 shows a perfect output in precision, recall, F1 score, and accuracy. On the other hand, models trained with a learning rate of 0.2 seem to result in lower F1 scores compared to other learning rates. The model trained using the SGD optimizer, relu as the activation function, and a learning rate of 0.2 shows the lowest value among the results.

### ***Dataset #2***

In the Dataset #2, the fonts were added noises by reversing selected random pixel. This results more hardly recognizable fonts even by human. Therefore, as shown in Table 2. the results of training did not generate any perfect model. The highest accuracy and F1 score were achieved by the model that was trained using the Adam and RMSprop optimizer algorithms, with learning rates of 0.001 and 0.01, and using the tanh and sigmoid activation functions. On the contrary, the lowest precision, recall, F1 score, and accuracy values were resulted from the training model that used RMSprop along with relu activation function and 0.2 learning rate. However, the majority of the results demonstrate good F1 scores and accuracy, successfully recognizing most of the test dataset.

The complete graphs depicting the training history of all models, including accuracy and validation accuracy, loss and validation loss, as well as the confusion matrix, are presented in figures below.

### ***Discussion***

As presented in Table 2., it can be seen that the model trained using learning rate of 0.01 reached the highest accuracy among other learning rates for both datasets, regardless of the types of optimizer algorithm and activation function used in that training. It can be concluded that a learning rate of 0.01 is optimal for training a model for font classification, even in the presence of noises. In Dataset #2, the result of training model using SGD as the optimizer function and tanh as the activation function along with 0.2 learning rate resulted in nearly perfect accuracy and F1 score. This contradicts the result of model trained using the RMSprop optimizer and relu activation function which produced worse accuracy and F1 score even when it used the same learning rate.

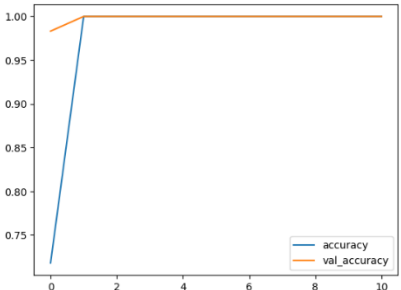
*Adam Optimizer*

**Training Results Using Adam Optimizer - Dataset #1**

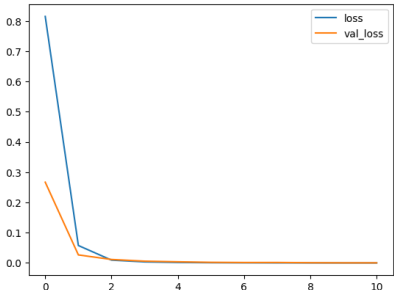
Learning rate: 0.001

Activation Function on 2nd layer: Relu

Accuracy & Val Accuracy



Loss & Val Loss



Confusion Matrix

Confusion matrix

	class A	class B	class C	class D	class E	class F	class G	
class A	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
class B	0 0.0%	90 14.15%	0 0.0%	0 0.0%	1 0.16%	0 0.0%	0 0.0%	91 98.90% 1.10%
class C	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
class D	0 0.0%	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
class E	0 0.0%	0 0.0%	0 0.0%	0 0.0%	89 13.99%	0 0.0%	0 0.0%	89 100% 0.00%
class F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	0 0.0%	93 100% 0.00%
class G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	93 100% 0.00%
sum_col	90 100% 0.00%	90 100% 0.00%	90 100% 0.00%	90 100% 0.00%	90 98.89% 1.11%	93 100% 0.00%	93 100% 0.00%	636 99.84% 0.16%
	class A	class B	class C	class D	class E	class F	class G	sum_lin

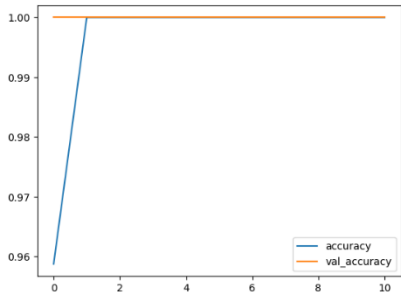
Actual

Accuracy:  
99.84%

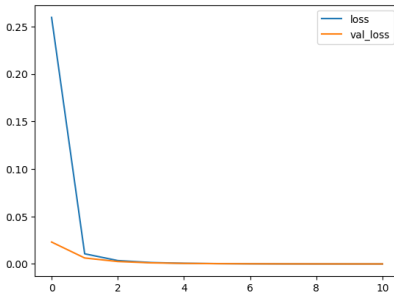
Learning rate: 0.01

Activation Function on 2nd layer: Sigmoid

Accuracy & Val Accuracy



Loss & Val Loss



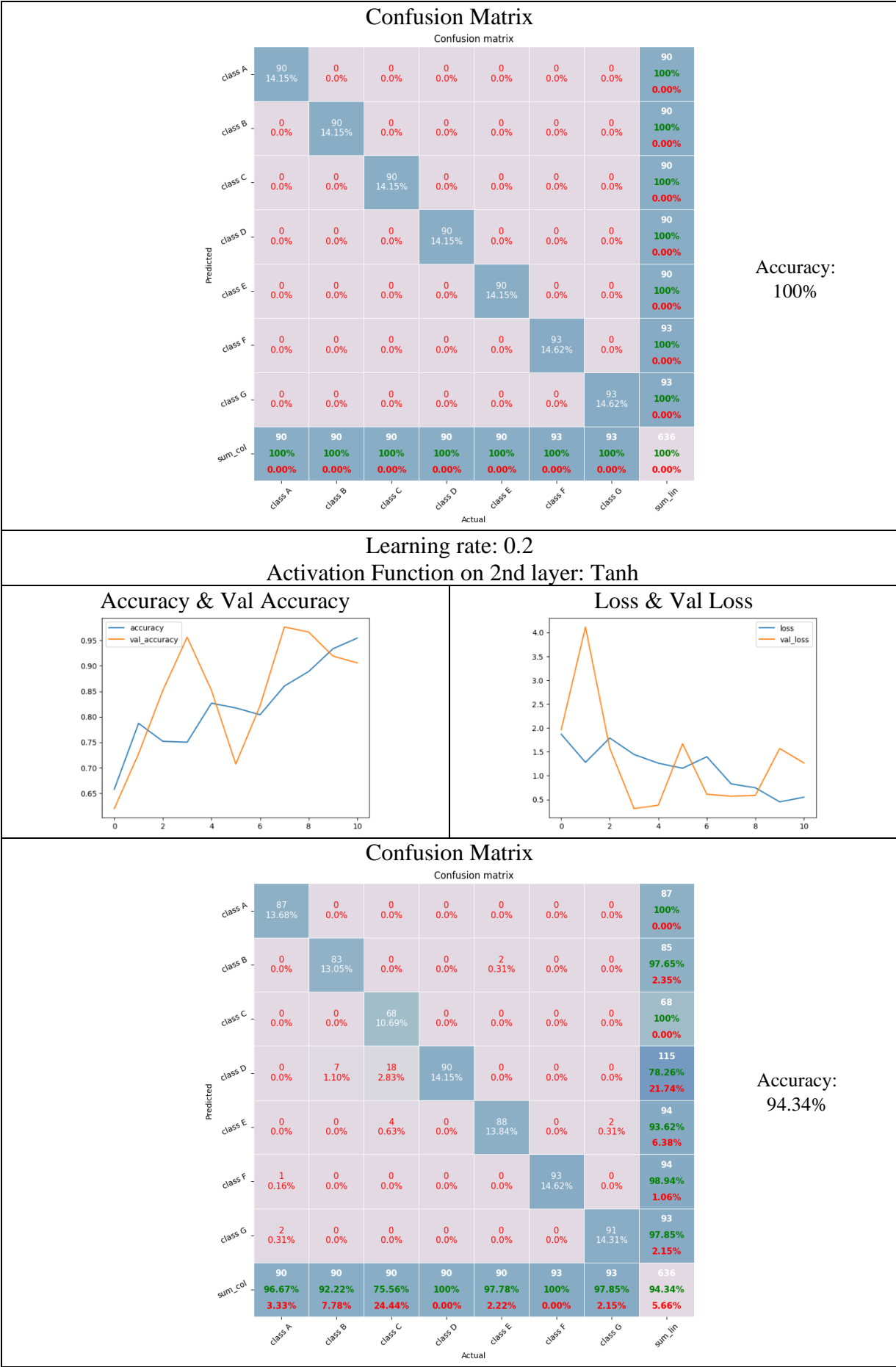


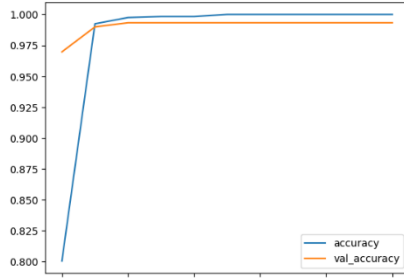
Figure 4.. Training results using Adam optimizer - Dataset #1

## Training Results Using Adam Optimizer - Dataset #2

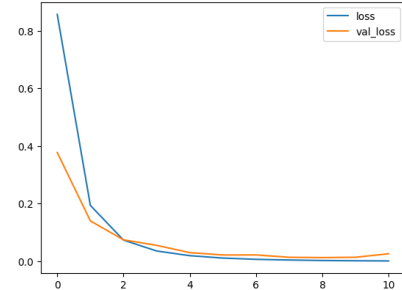
Learning rate: 0.001

Activation Function on 2nd layer: Tanh

Accuracy & Val Accuracy



Loss & Val Loss



Confusion Matrix

Confusion matrix

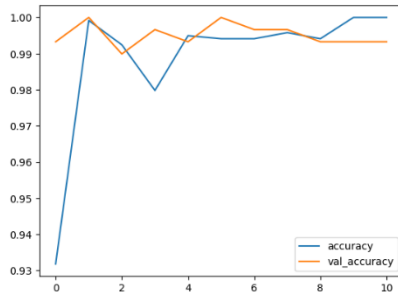
	class A	class B	class C	class D	class E	class F	class G	
class A	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
class B	0 0.0%	89 13.99%	0 0.0%	1 0.16%	0 0.0%	0 0.0%	0 0.0%	90 98.89% 1.11%
class C	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
class D	0 0.0%	0 0.0%	0 0.0%	89 13.99%	0 0.0%	0 0.0%	0 0.0%	89 100% 0.00%
class E	0 0.0%	1 0.16%	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	91 98.90% 1.10%
class F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	0 0.0%	93 100% 0.00%
class G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	93 100% 0.00%
sum_col	90	90	90	90	90	93	93	636
	100%	98.89%	100%	98.89%	100%	100%	100%	99.69%
	0.00%	1.11%	0.00%	1.11%	0.00%	0.00%	0.00%	0.31%
	class A	class B	class C	class D	class E	class F	class G	sum_lin
Predicted								
Actual								

Accuracy:  
99.69%

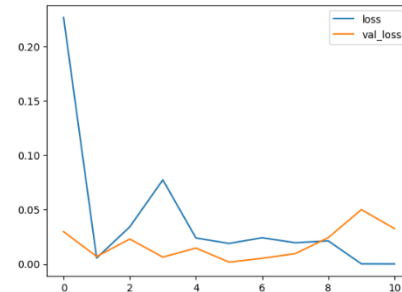
Learning rate: 0.01

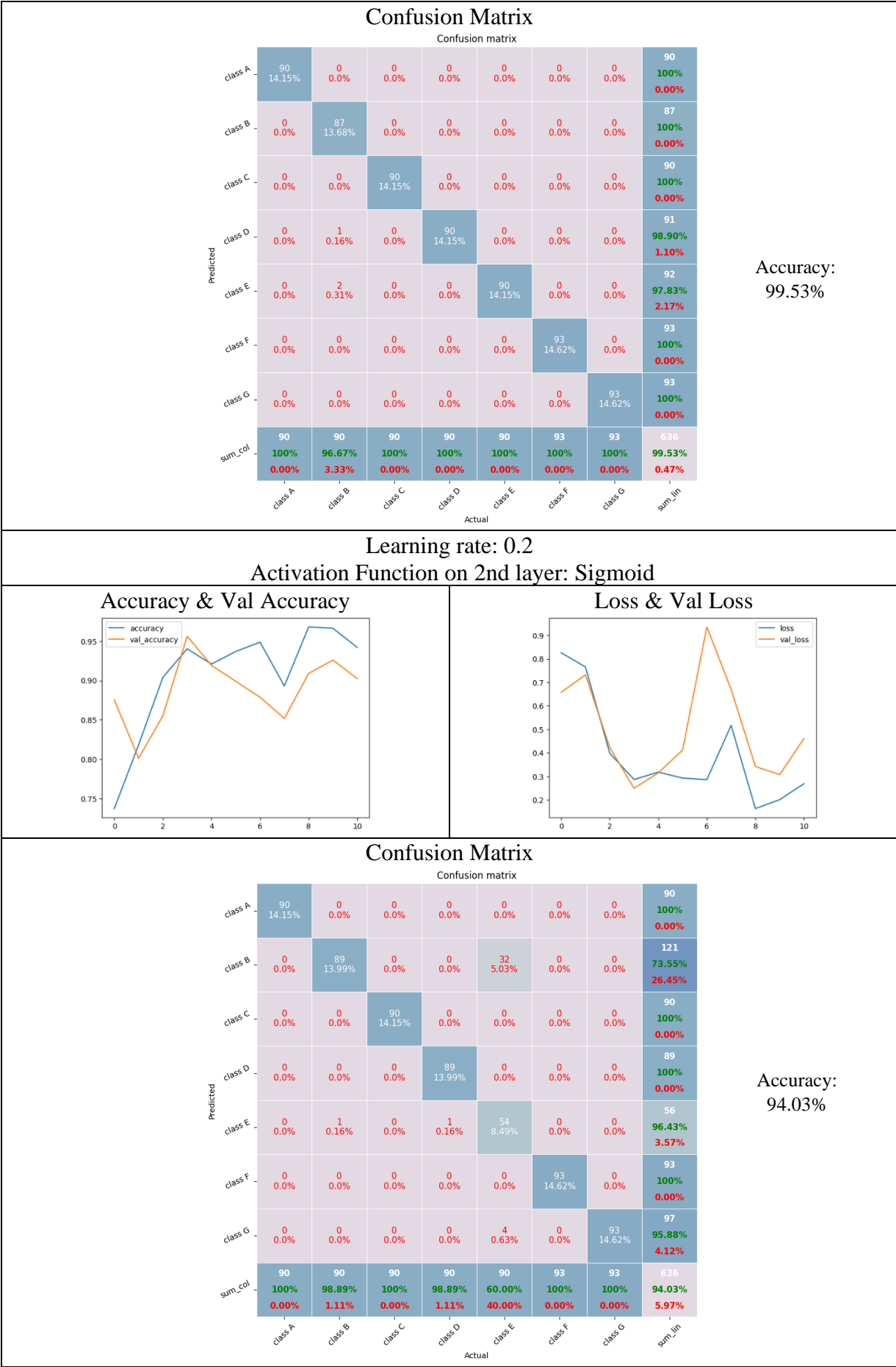
Activation Function on 2nd layer: Relu

Accuracy & Val Accuracy

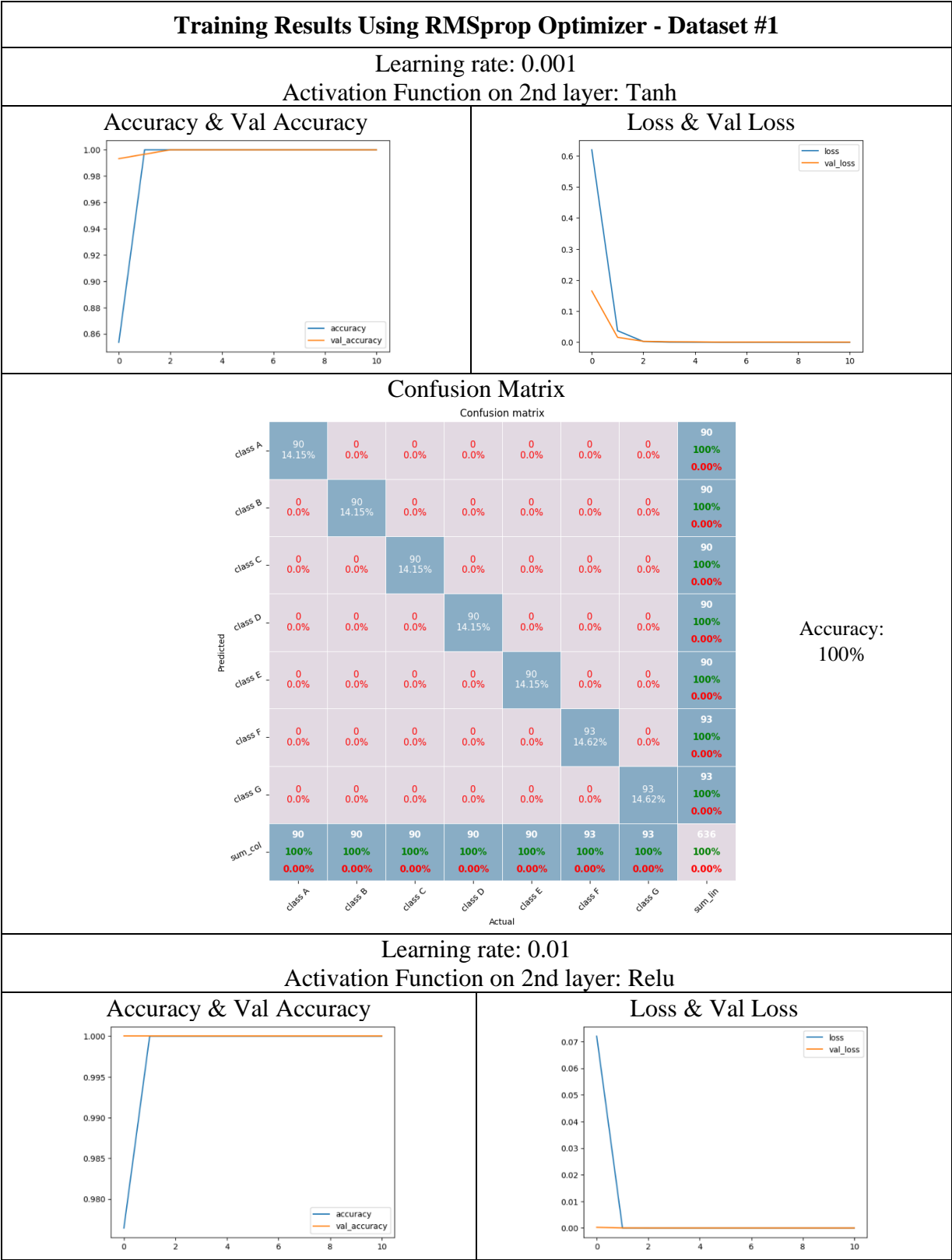


Loss & Val Loss





RMSprop Optimizer





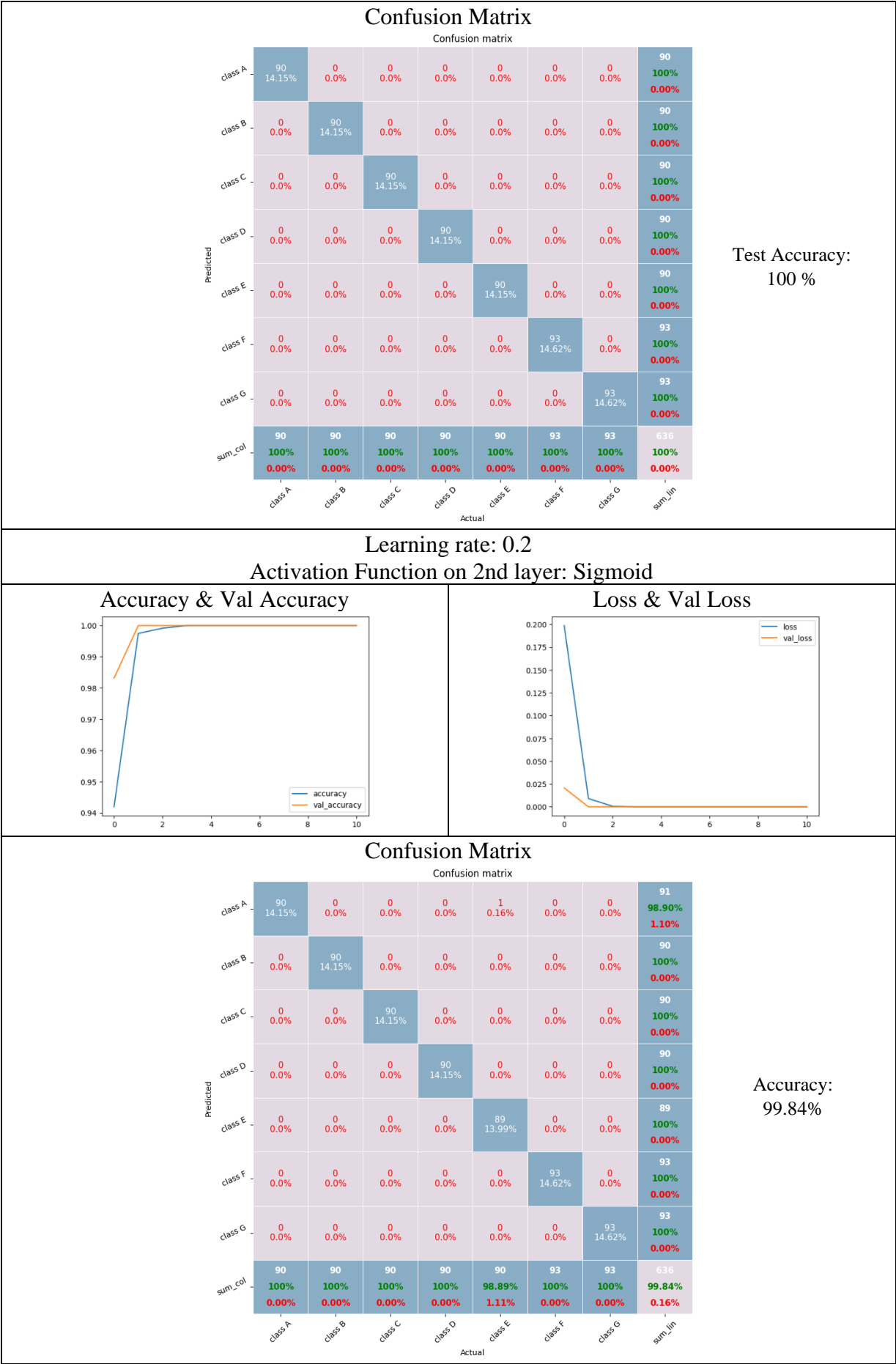


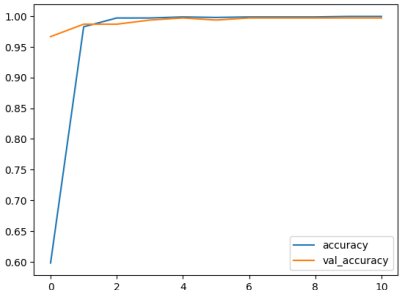
Figure 6. Training results using RMSprop optimizer - Dataset #1

Training Results Using RMSprop Optimizer - Dataset #2

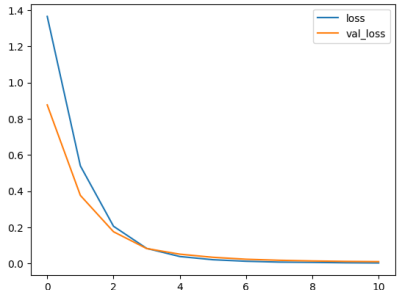
Learning rate: 0.001

Activation Function on 2nd layer: Sigmoid

Accuracy & Val Accuracy



Loss & Val Loss



Confusion Matrix

Confusion matrix

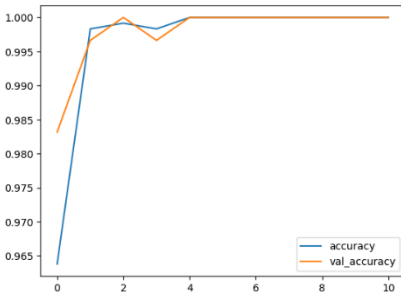
Predicted	class A	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
	class B	0 0.0%	89 13.99%	0 0.0%	0 0.0%	1 0.16%	0 0.0%	0 0.0%	90 98.89% 1.11%
	class C	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
	class D	0 0.0%	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	0 0.0%	90 100% 0.00%
	class E	0 0.0%	1 0.16%	0 0.0%	0 0.0%	89 13.99%	0 0.0%	0 0.0%	90 98.89% 1.11%
	class F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	0 0.0%	93 100% 0.00%
	class G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	93 14.62%	93 100% 0.00%
	sum_col	90 100% 0.00%	90 98.89% 1.11%	90 100% 0.00%	90 100% 0.00%	90 98.89% 1.11%	93 100% 0.00%	93 100% 0.00%	636 99.69% 0.31%
		Actual							
		class A	class B	class C	class D	class E	class F	class G	sum_row

Test Accuracy:  
99.69%

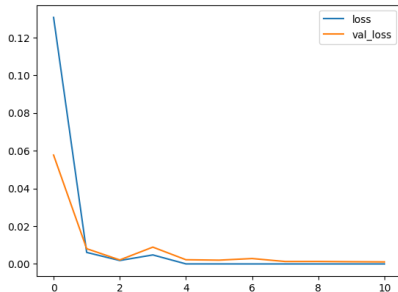
Learning rate: 0.01

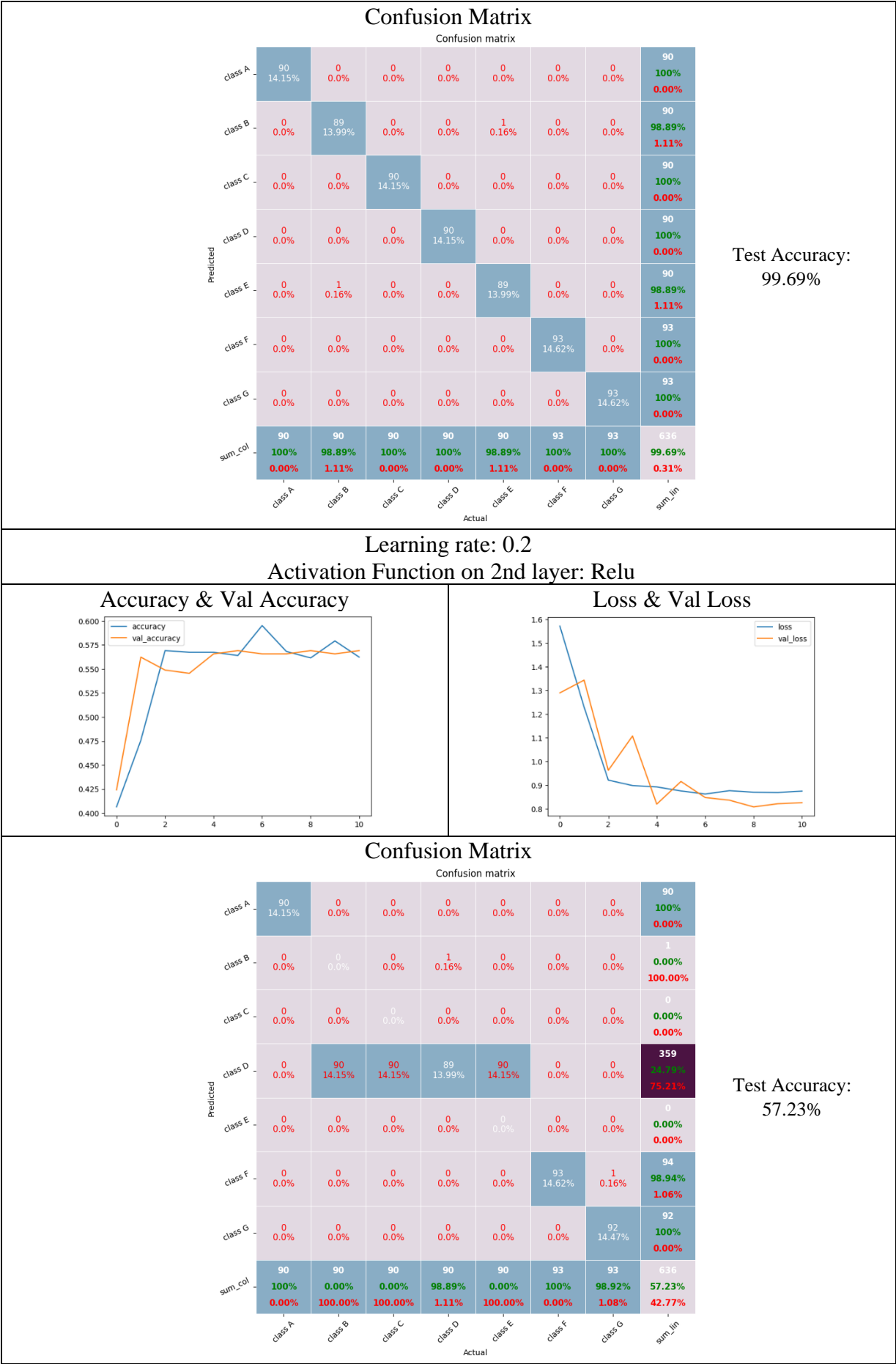
Activation Function on 2nd layer: Tanh

Accuracy & Val Accuracy

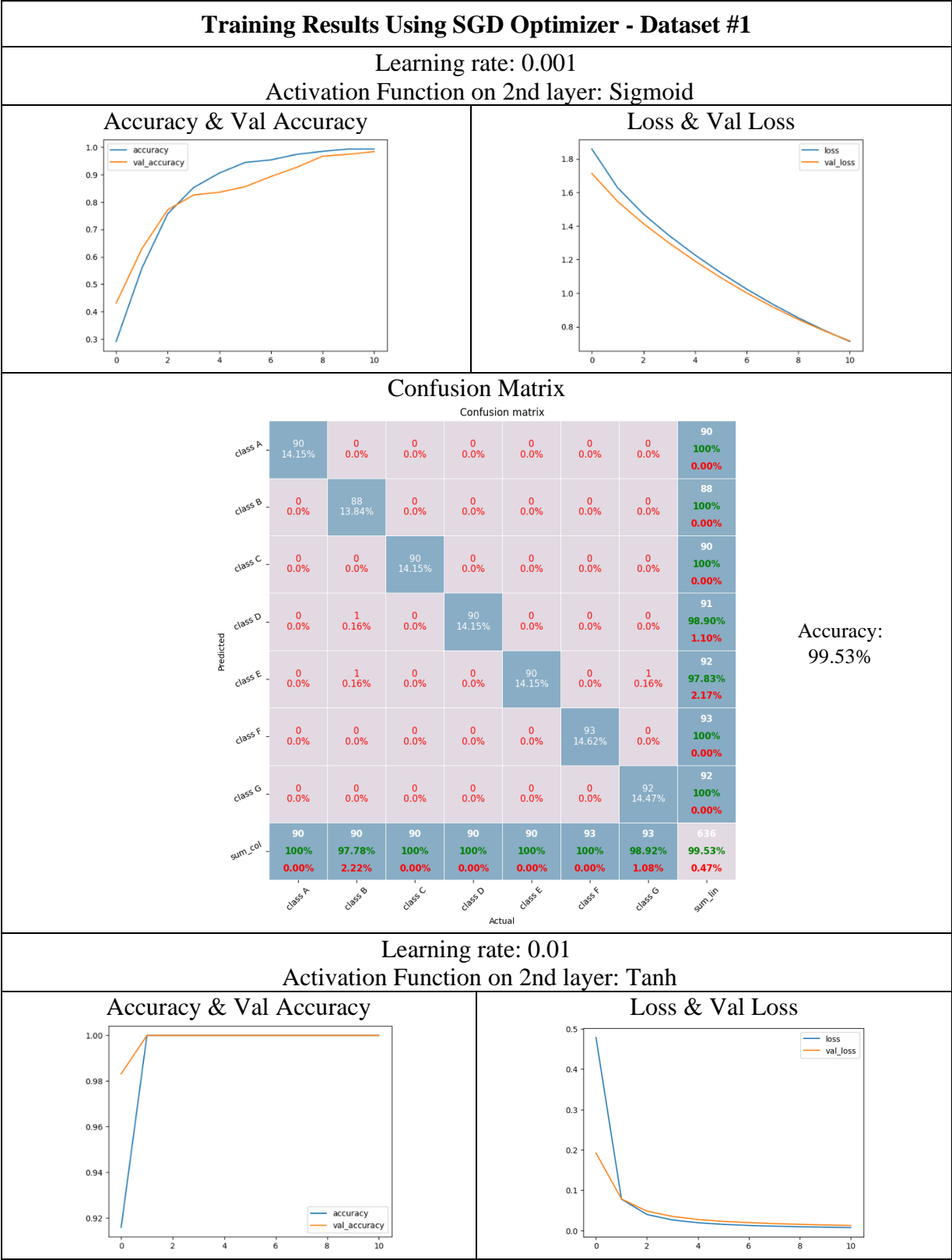


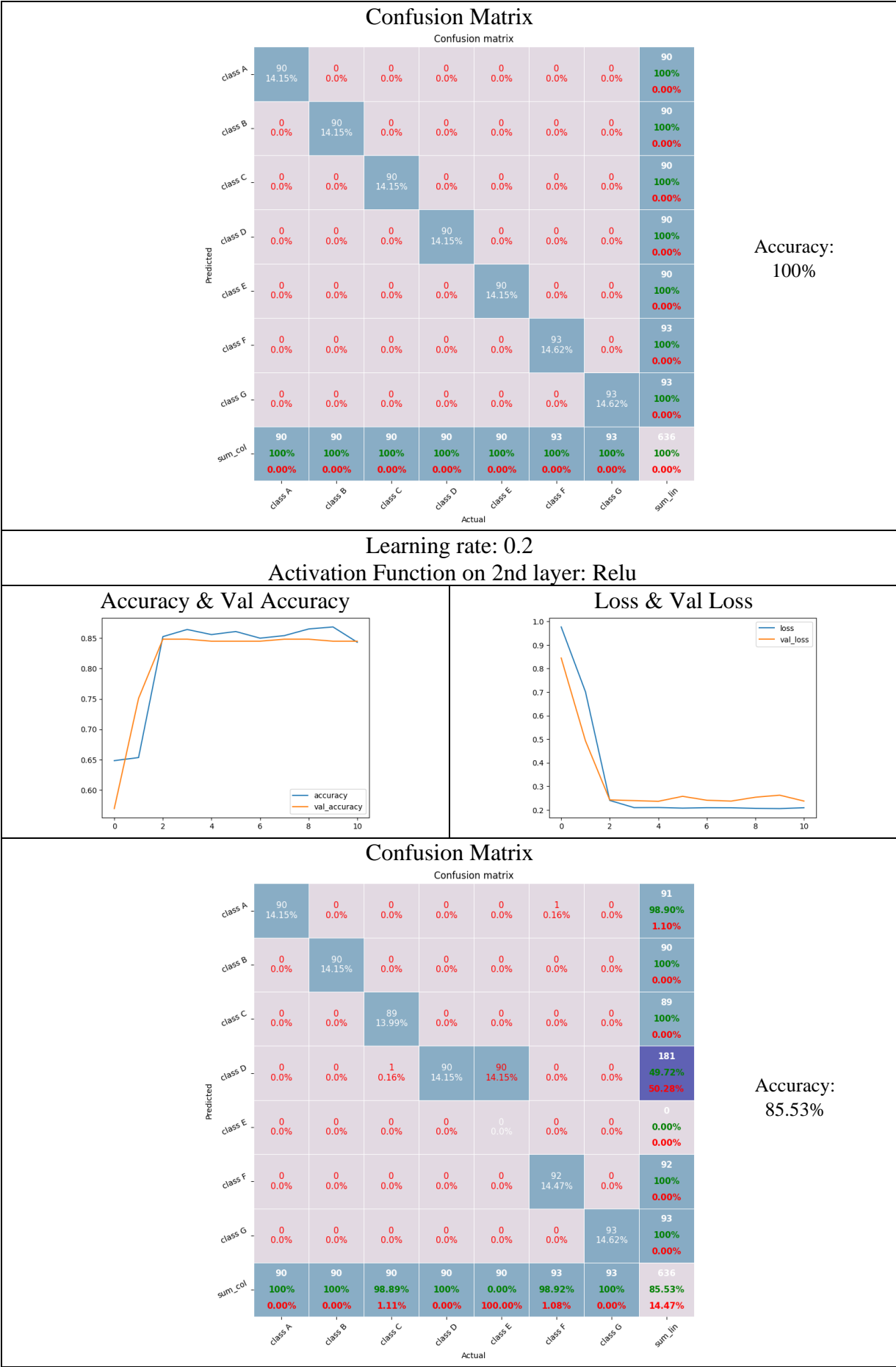
Loss & Val Loss





SGD Optimizer



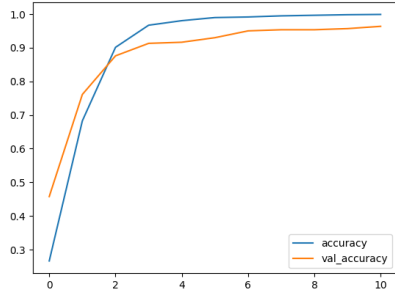


## Training Results Using SGD Optimizer - Dataset #2

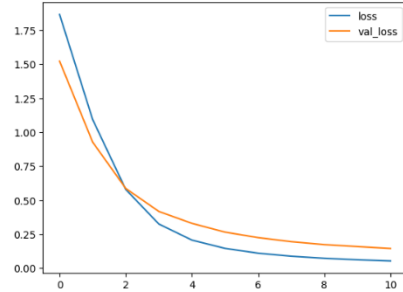
Learning rate: 0.001

Activation Function on 2nd layer: Relu

Accuracy & Val Accuracy



Loss & Val Loss



### Confusion Matrix

Confusion matrix

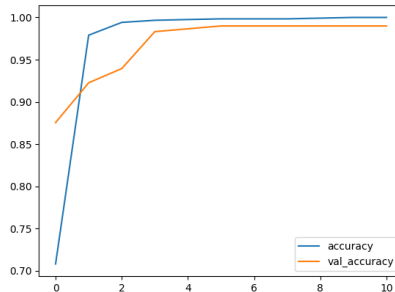
	class A	class B	class C	class D	class E	class F	class G	
class A	90 14.15%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.16%	91 98.90% 1.10%
class B	0 0.0%	87 13.68%	0 0.0%	1 0.16%	1 0.16%	0 0.0%	0 0.0%	89 97.75% 2.25%
class C	0 0.0%	0 0.0%	90 14.15%	0 0.0%	0 0.0%	1 0.16%	0 0.0%	91 98.90% 1.10%
class D	0 0.0%	2 0.31%	0 0.0%	89 13.99%	0 0.0%	0 0.0%	0 0.0%	91 97.80% 2.20%
class E	0 0.0%	1 0.16%	0 0.0%	0 0.0%	89 13.99%	0 0.0%	2 0.31%	92 96.74% 3.26%
class F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	92 14.47%	0 0.0%	92 100% 0.00%
class G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90 14.15%	90 100% 0.00%
sum_col	90 100% 0.00%	90 96.67% 3.33%	90 100% 0.00%	90 98.89% 1.11%	90 98.89% 1.11%	93 98.92% 1.08%	93 96.77% 3.23%	636 98.58% 1.42%
	class A	class B	class C	class D	class E	class F	class G	sum_lin
Predicted								
Actual								

Test Accuracy:  
98.58%

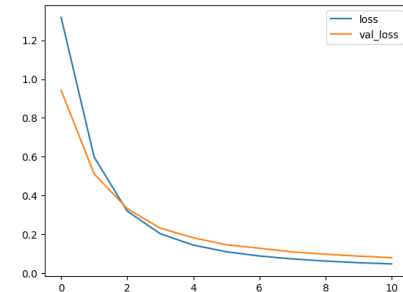
Learning rate: 0.01

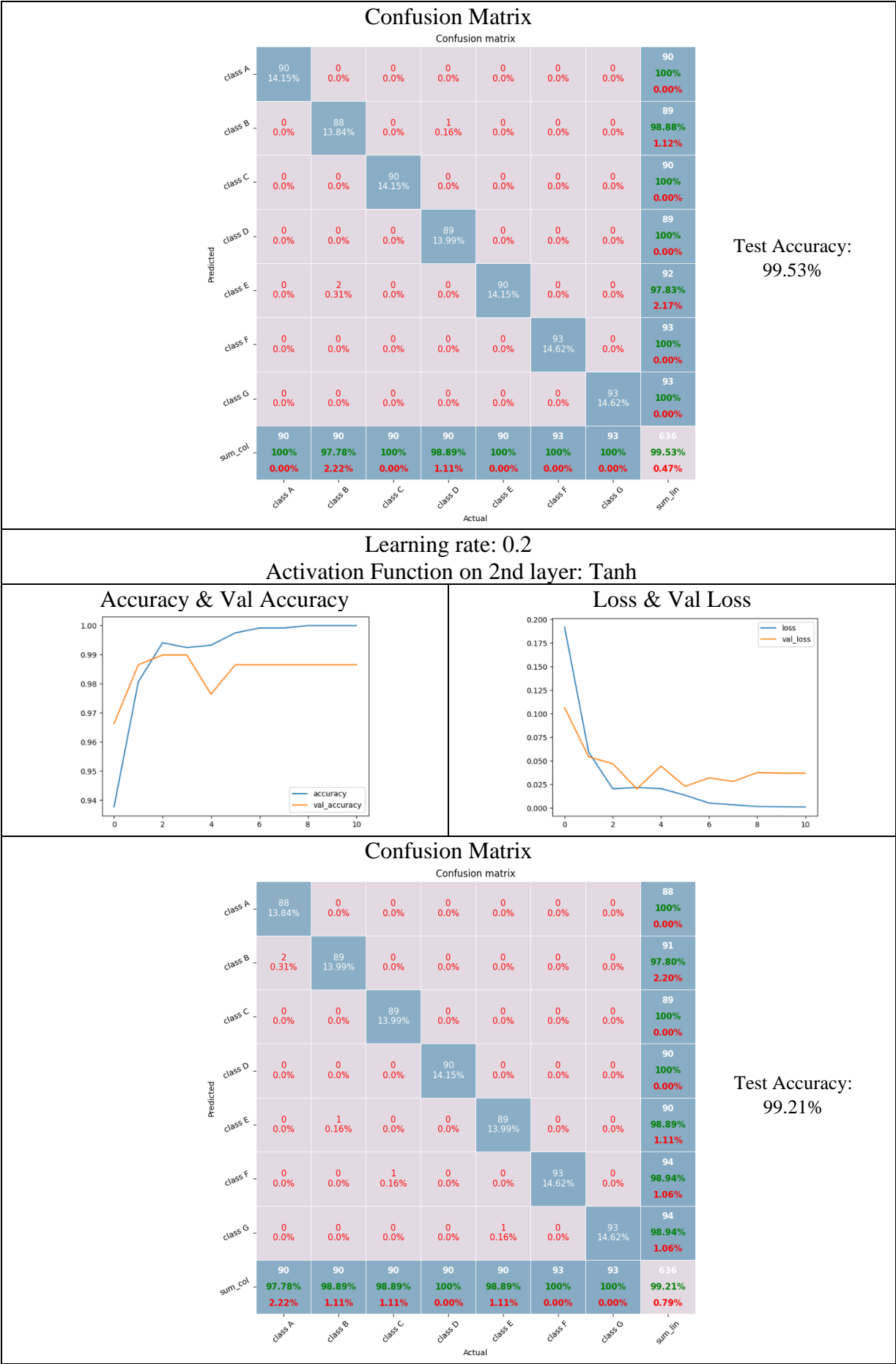
Activation Function on 2nd layer: Sigmoid

Accuracy & Val Accuracy



Loss & Val Loss





## **Project Link**

<https://colab.research.google.com/drive/1tqy1Zfy956cdJHTC IrYkpc2y3rOCarAI>