Assignment3

May 16, 2025

1 Computer Vision 2025 Assignment 3: Deep Learning for Perception Tasks

This assignment contains 2 questions. The first question probes understanding of deep learning for classification. The second question requires you to write a short description of a Computer Vision method. You wil need to submit two separate PDF files, one for each question.

All results presented in this report represent the average of three independent trials conducted using the same data and parameters.

1.1 Question 1: A Simple Classifier *(20 marks, 60%)*

For this exercise, we provide demo code showing how to train a network on a small dataset called Fashion-MNIST. Please run through the code *"tutorial-style"* to get a sense of what it is doing. Then use the code alongside lecture notes and other resources to understand how to use pytorch libraries to implement, train and use a neural network. For the Fashion-MNIST dataset the labels from 0-9 correspond to various clothing classes so you might find it convenient to **create a python list as follows:**

class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

You will need to answer various questions about the system, how it operates, the results of experiments with it and make modifications to it yourself. You can change the training scheme and the network structure. Organise your own text and code cell to show the answer of each question below. **Detailed requirements:**

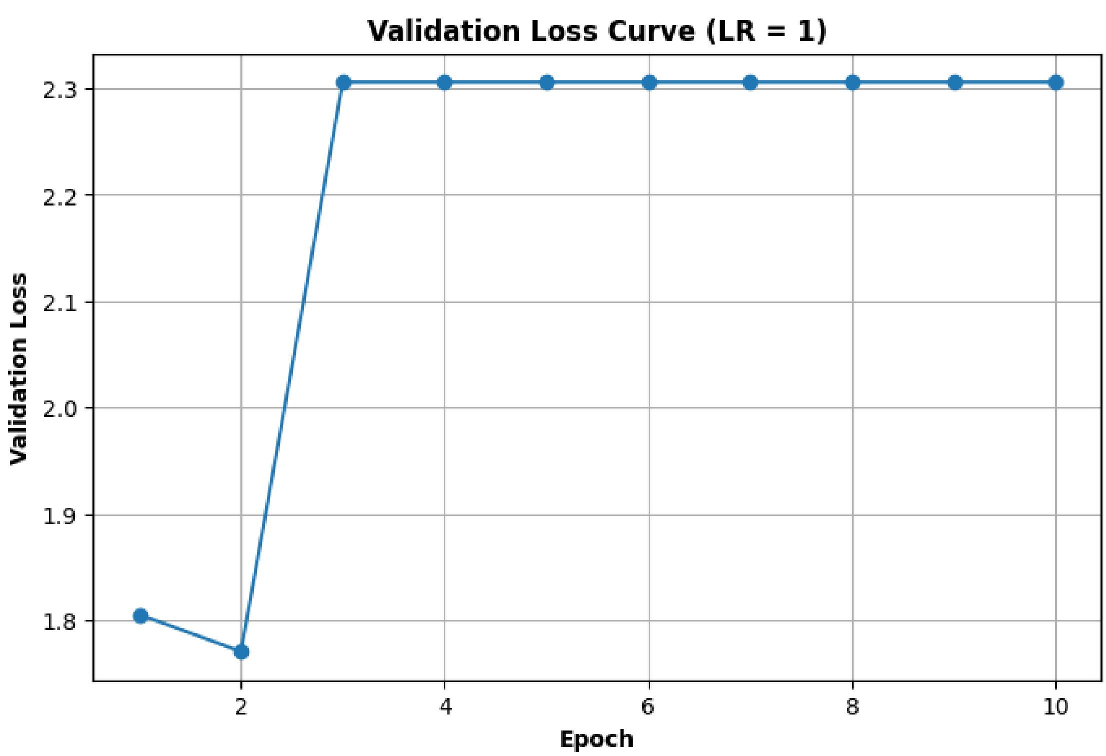
1.1.1 Q1.1 *(1 Point)*

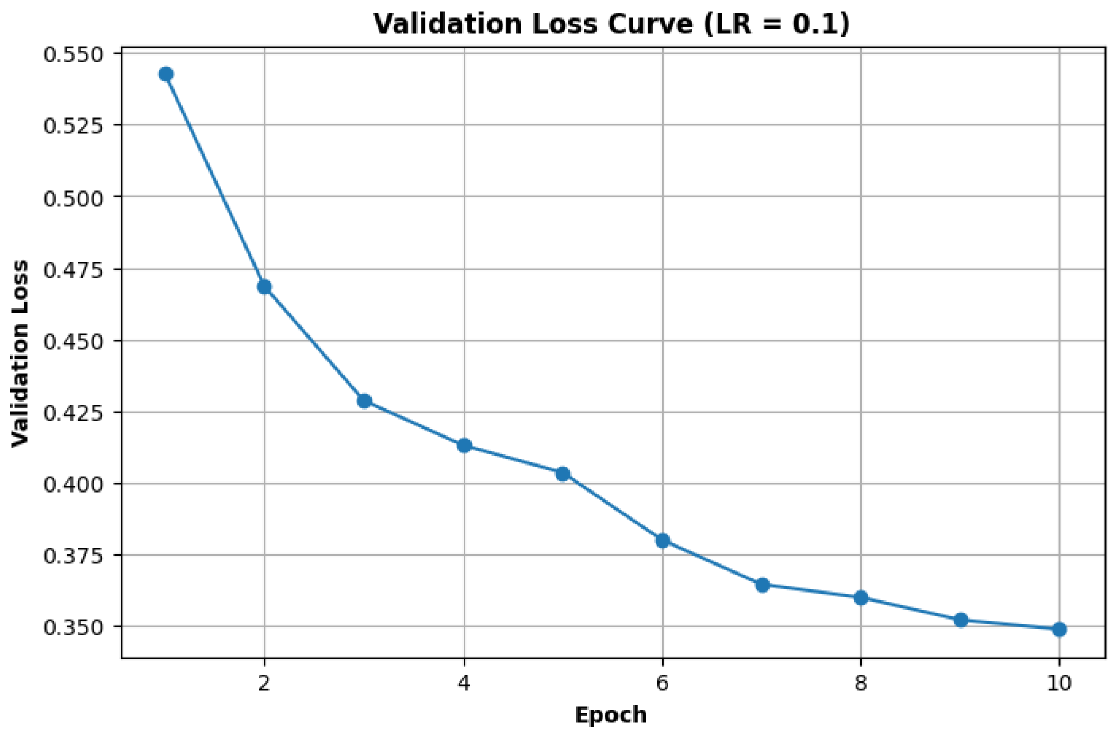
Extract 3 images of different types of clothing from the training dataset, print out the size/shape of the training images, and display the three with their corresponding labels.

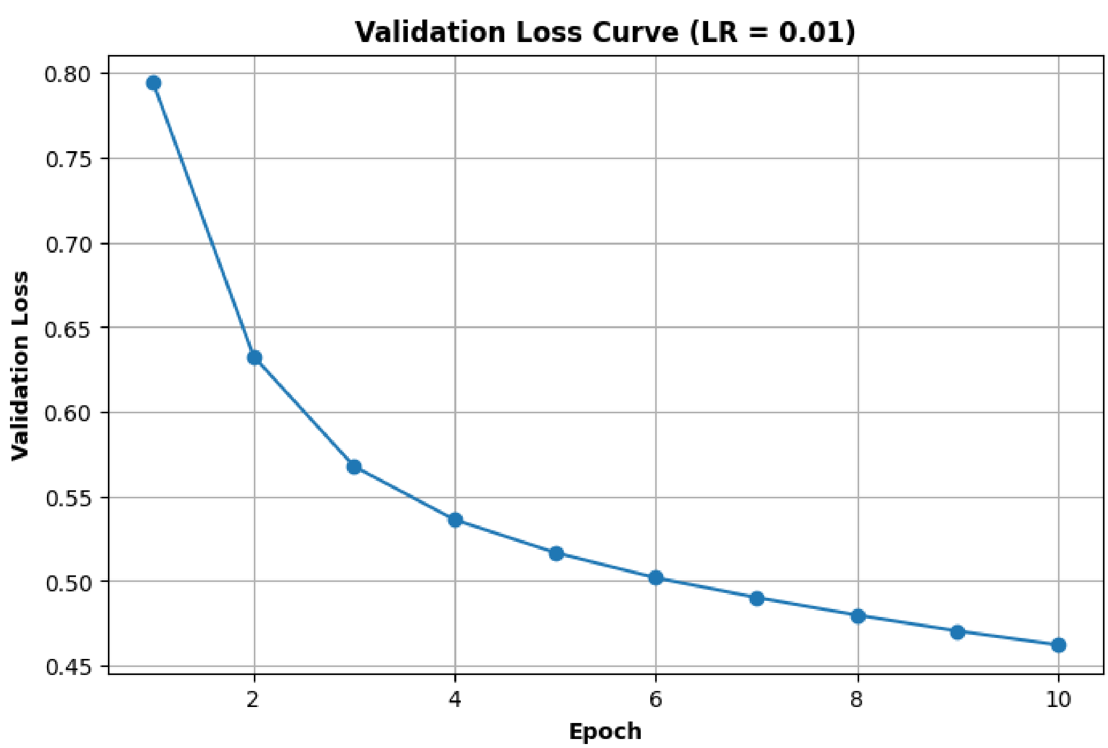
1.1.2 Q1.2 *(2 Points)*

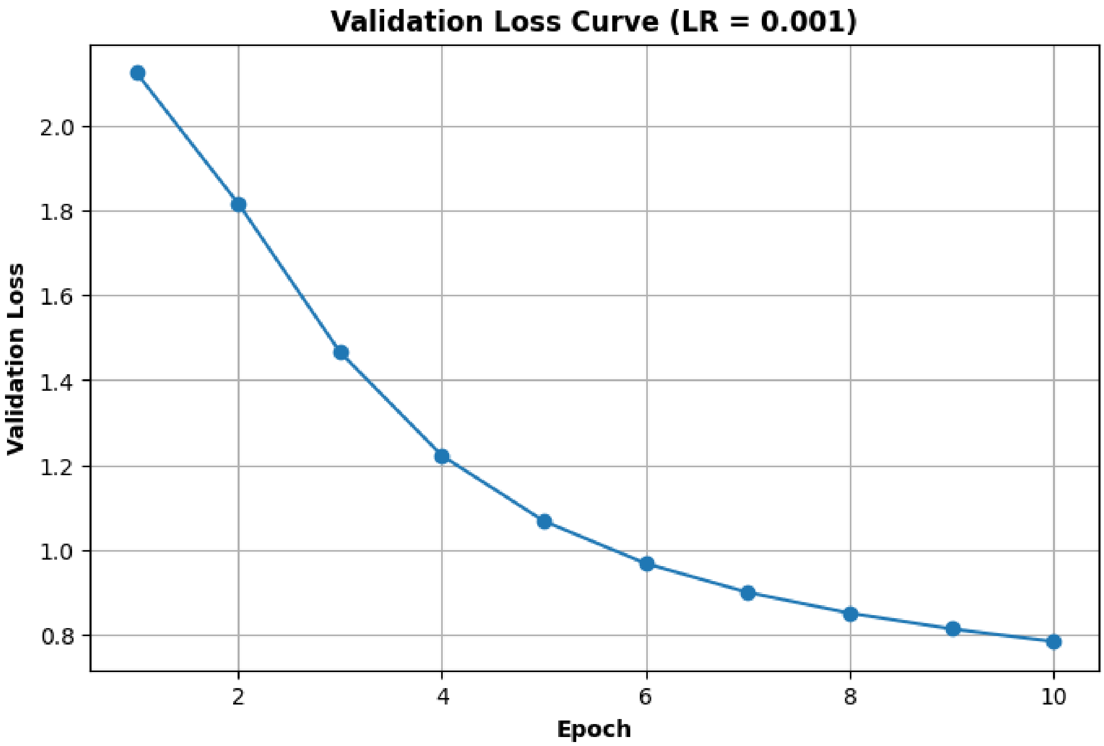
Run the training code for 10 epochs, for different values of the learning rate. **Fill in the table below and plot the loss curves for each experiment:**

LR	Accuracy
1	10.00%
0.1	87.40%
0.01	83.40%
0.001	70.80%




Validation Loss Curve (LR = 0.1)
Validation Loss
0.550
0.525
0.500
0.475
0.450
0.425
0.400
0.375
0.350
2
4
6
8
10
Epoch

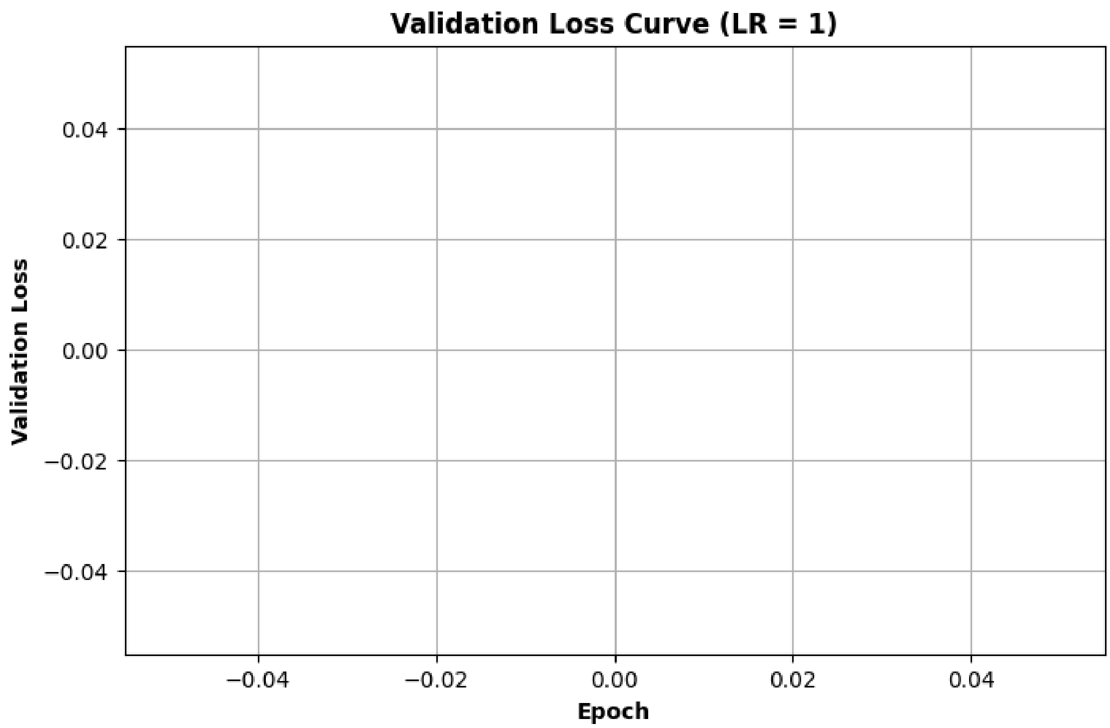

Validation Loss Curve (LR = 0.01)
Validation Loss
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
2
4
6
8
10
Epoch



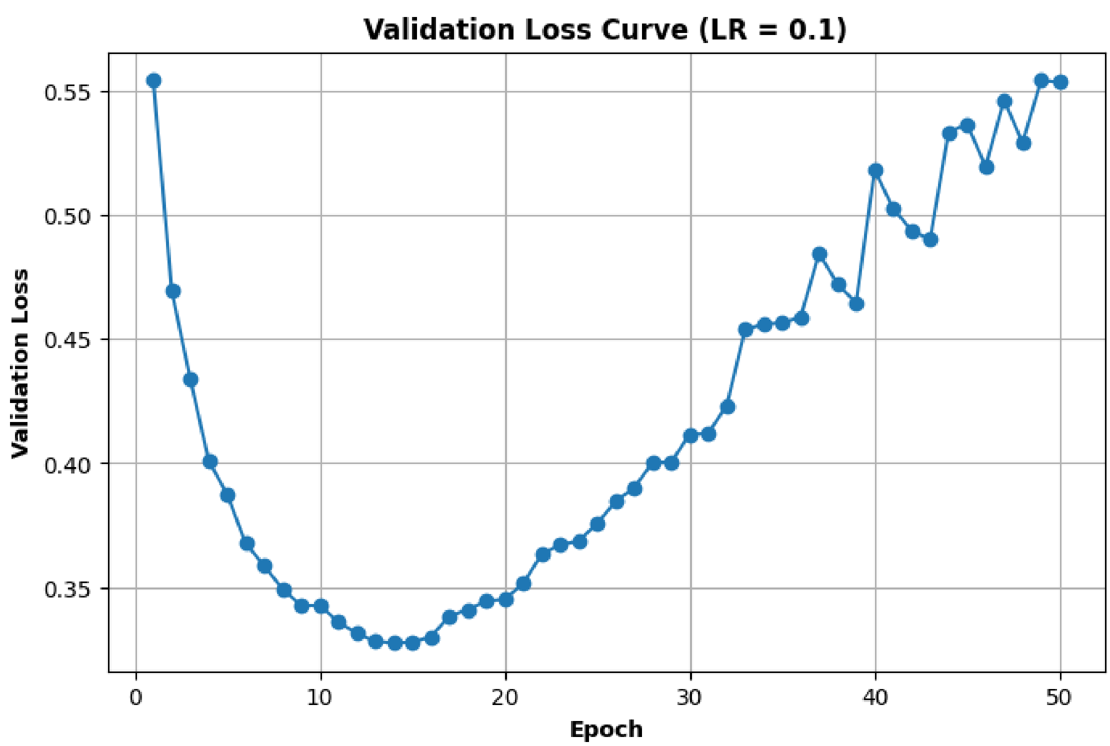
1.1.3 Q1.3 *(3 Points)*

Report the number of epochs when the network converges *(or number of epochs for the best accuracy, if it fails to converge)*. Fill in the table below and plot the loss curve for each experiment. **Please run the code for more than 10 epochs *(e.g. 50 or 100)* and report when you observe convergence:**

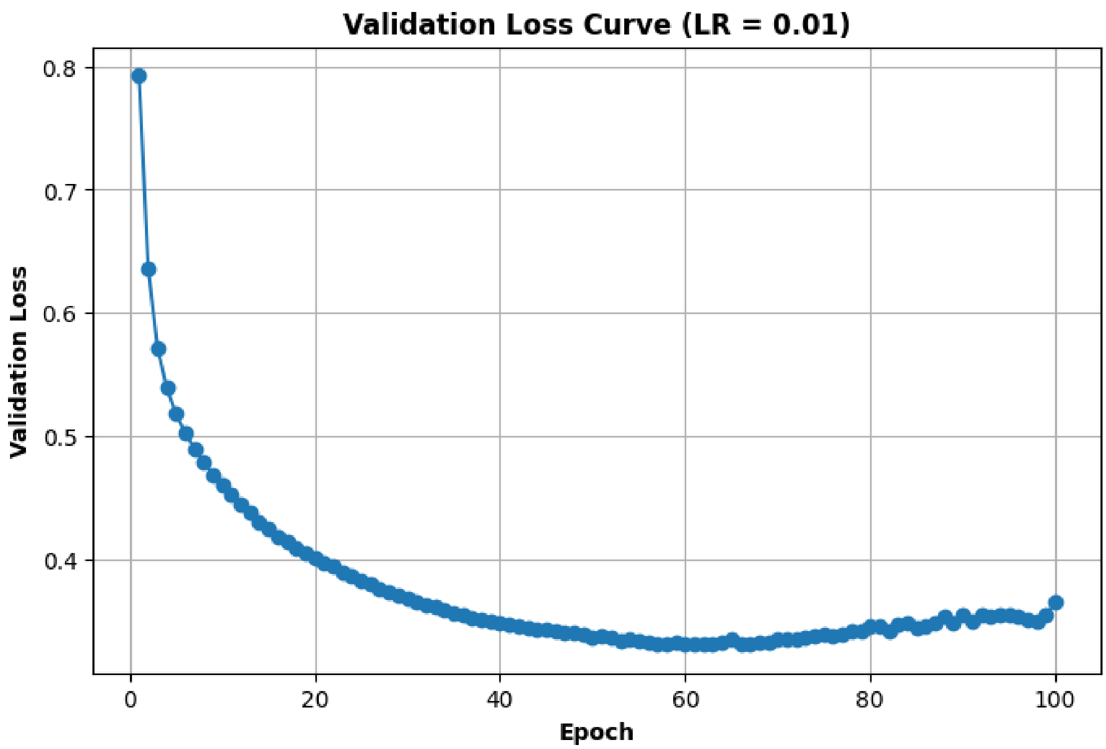
LR	Accuracy	Epoch
1	NaN	NaN
0.1	88.20%	14
0.01	87.80%	60
0.001	84.60%	>100

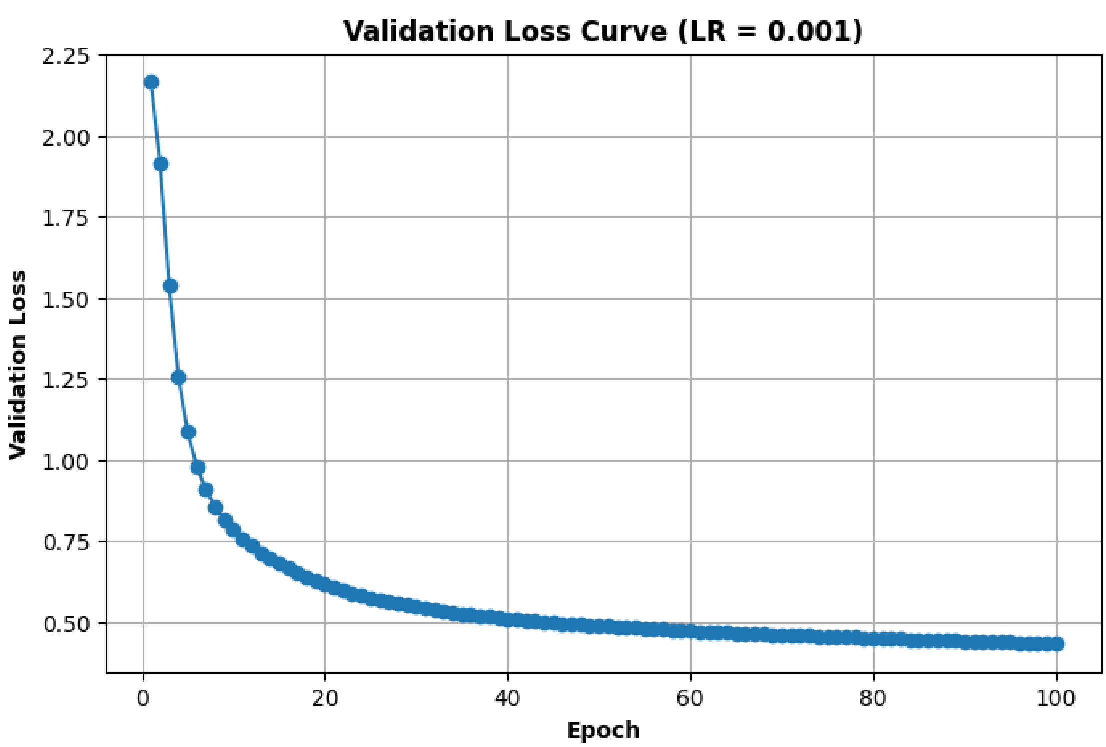


Validation Loss Curve (LR = 1)
Validation Loss
0.04
0.02
0.00
−0.02
−0.04
−0.04
−0.02
0.00
0.02
0.04
Epoch



Validation Loss Curve (LR = 0.1)
Validation Loss
0.55
0.50
0.45
0.40
0.35
0
10
20
30
40
50
Epoch


Validation Loss Curve (LR = 0.01)
Validation Loss
Epoch
0.8
0.7
0.6
0.5
0.4
0
20
40
60
80
100


Validation Loss Curve (LR = 0.001)
Validation Loss
Epoch
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0
20
40
60
80
100

1.1.4 Q1.4 *(2 Points)*

Compare the results in table 1 and table 2, what is your observation and your understanding of learning rate?

Upon examining the results from Tables 1 and 2, a few key observations can be made about the effect of the learning rate on training and convergence. A learning rate of 1 is excessively high, leading to unstable and unreliable training behavior. In the 10-epoch evaluation, the model consistently achieved 10% accuracy *(likely equivalent to random guessing)* indicating that no meaningful learning occurred. Furthermore, in the convergence test, training either diverged *(resulting in NaN values as seen above)* or quickly plateaued at 10% accuracy within approximately 12 epochs. This phenomenon occurs due to exploding gradients, where large weight updates cause the model to overshoot and fail to converge. Overall, this suggests that the learning rate was too large for the model to converge effectively, leading it to fail to maintain stability during training. Unfortunately, the resulting data is not particularly informative for assessing model performance.

Additionally, the learning rate of 0.1 produces the highest accuracy *(87.40% on average)* within the first 10 epochs, as shown in Table 1. This value strikes a balance between large enough updates to quickly reduce loss, but not so large that it overshoots optimal points. The model converges to the best accuracy *(~88.20%)* in approximately 14 epochs, as confirmed in Table 2. This learning rate is ideal for quick yet stable convergence, which is why the accuracy is higher compared to smaller learning rates.

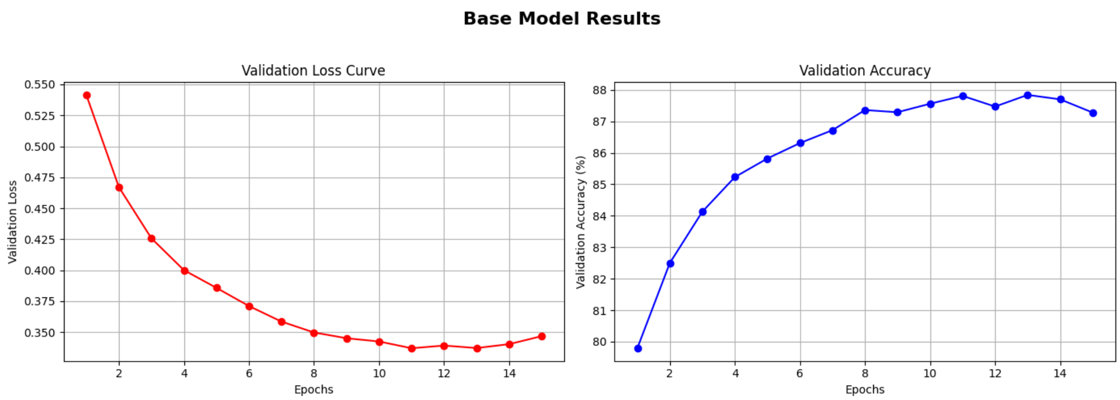
With a learning rate of 0.01, the model requires more time to converge, as it makes smaller, more stable updates. While this rate leads to a lower accuracy *(83.40% on average)* in 10 epochs, it performs much closer to the 0.1 learning rate with extended training *(~60 epochs gives 87.8% on average)*. However, the model still takes longer to converge compared to 0.1, suggesting that small learning rates can lead to slow progress but a more refined convergence over time. This is evident in the smooth gradient of the loss curve. Finally, a learning rate of 0.001 is very small and results in slow convergence. The model's accuracy remains low in the first 10 epochs *(70.80% on average)* and takes over 100 epochs to completely converge, achieving an accuracy of around 84.60% after 100 epochs. While this rate offers stability, it also illustrates that extremely slow updates may not allow the model to reach its potential within a reasonable amount of time.

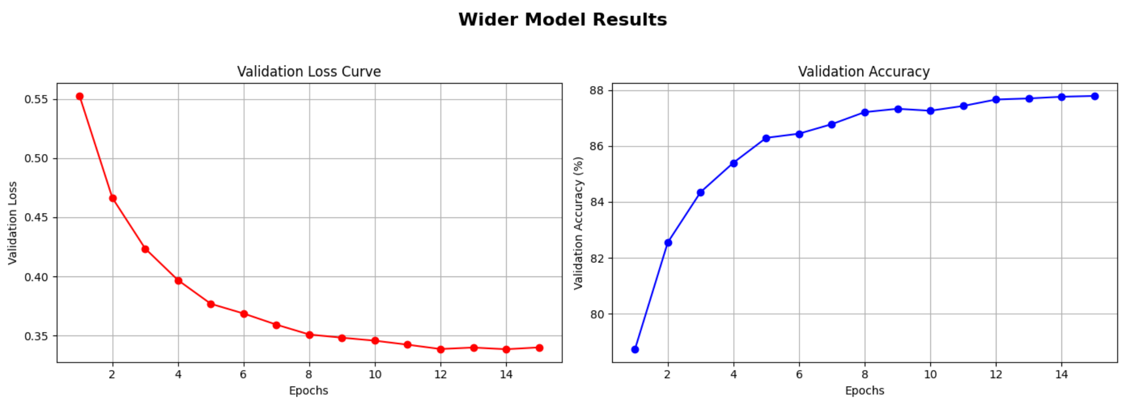
Overall, comparing the results in Table 1 and Table 2, it is clear that the learning rate has a significant impact on both training stability and convergence speed. A learning rate of 1 is too high, causing unstable updates and divergence due to exploding gradients, often resulting in NaN losses. In contrast, a very low learning rate like 0.001 ensures stability but requires far more epochs to converge, leading to lower accuracy within a limited training window. The optimal performance in this experiment was achieved with a learning rate of 0.1, which balanced convergence speed and training stability, reaching a maximum accuracy of approximately 88% in just 14 epochs. This suggests that 0.1 is well-tuned for the current model and dataset. However, the observed accuracy plateau also indicates a possible limitation of the model's capacity. Future improvements could involve modifying the network architecture, such as adjusting the number of hidden layers or neurons, to better capture complex data patterns and potentially exceed the current performance ceiling. Ultimately, this experiment highlights the importance of selecting an appropriate learning rate, as it directly influences not just how fast a model learns but whether it learns at all.

1.1.5 Q1.5 *(5 Points)*

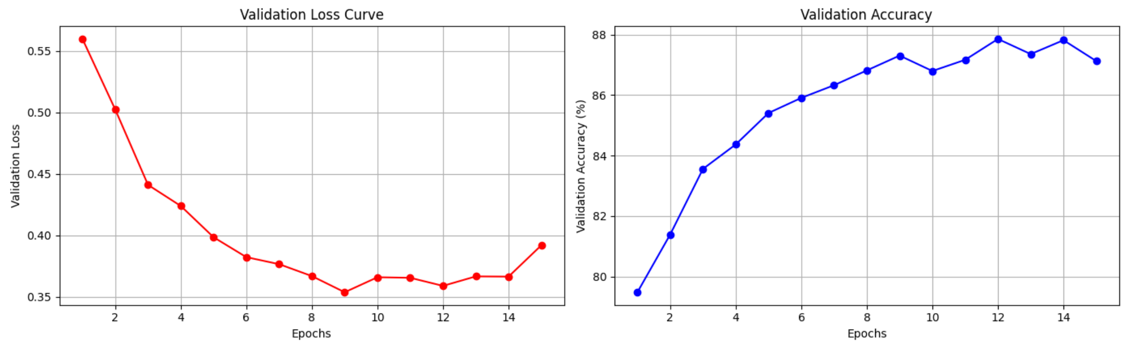
Build a wider network by modifying the code that constructs the network so that the hidden layer(s) contain more perceptrons, and record the accuracy along with the number of trainable parameters in your model. Now modify the original network to be deeper instead of wider ***(i.e.** by adding more hidden layers)*. Record your accuracy and network size findings. Plot the loss curve for each experiment. Also plot the test accuracy and loss for both the wider and deeper architectures and discuss what you observe. **Write down your conclusions about changing the network structure.**

Structures	Accuracy	Parameters
Base	86.50%	669,706
Deeper	87.40%	830,090
Wider	88.20%	1,863,690





Deeper Model Results



The base model employed in this experiment uses a standard fully connected architecture with two hidden layers of 512 neurons each, achieving a strong test accuracy of 86% on average. The learning rate was set to 0.1, and the model was trained over 15 epochs. These hyperparameters were chosen based on their ability to provide fast and stable convergence on the relatively simple FashionMNIST dataset, as seen in the discussion above. These parameters also achieve reasonable results while keeping the model training within the hardware constraints of this project. With 669,706 trainable parameters, the base model strikes a healthy balance between model complexity and performance. The validation curves for both loss and accuracy demonstrated reasonably smooth convergence, indicating effective learning.

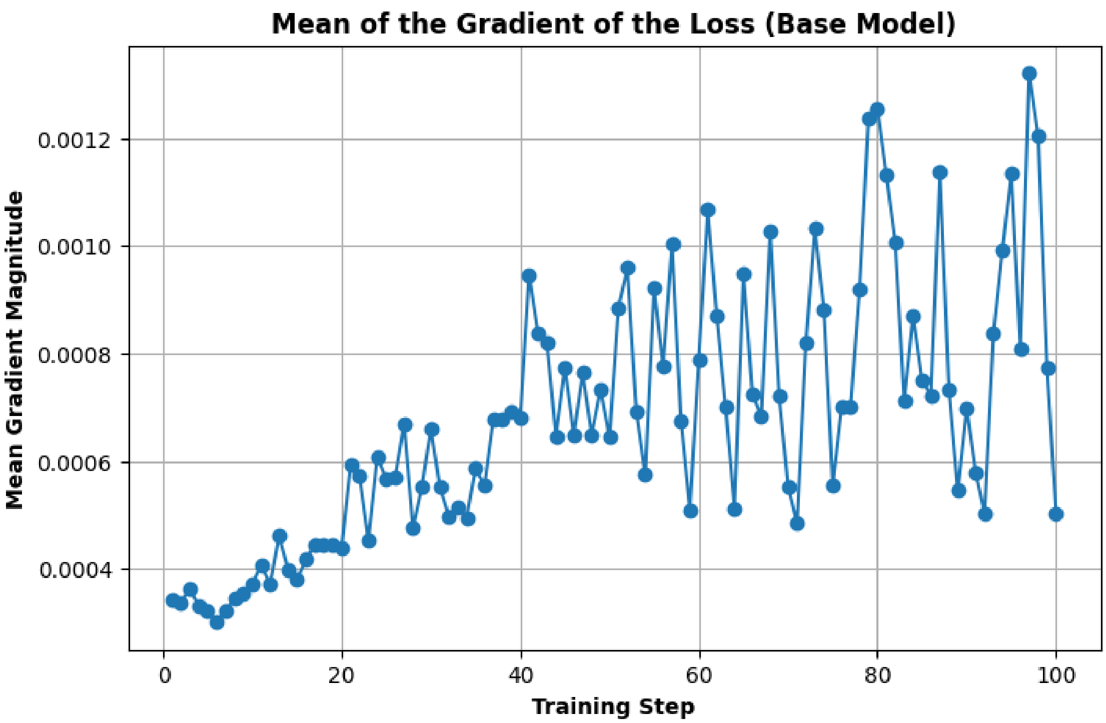
To explore the impact of model width, the number of neurons in each hidden layer was doubled to 1024, significantly increasing the trainable parameters to 1,863,690. The wider model achieved a higher test accuracy of 88.20%, compared to 86.50% for the base model, indicating a modest but meaningful improvement. Additionally, the wider model displayed smoother training dynamics. This is evident in the loss decreasing more steadily, and the accuracy increasing with less fluctuation compared to the base model. This suggests that the wider network facilitated better gradient flow and optimisation stability. While the performance gain was not dramatic, it shows that the wider network was able to extract more information from the data, providing a small generalisation benefit on the FashionMNIST dataset.

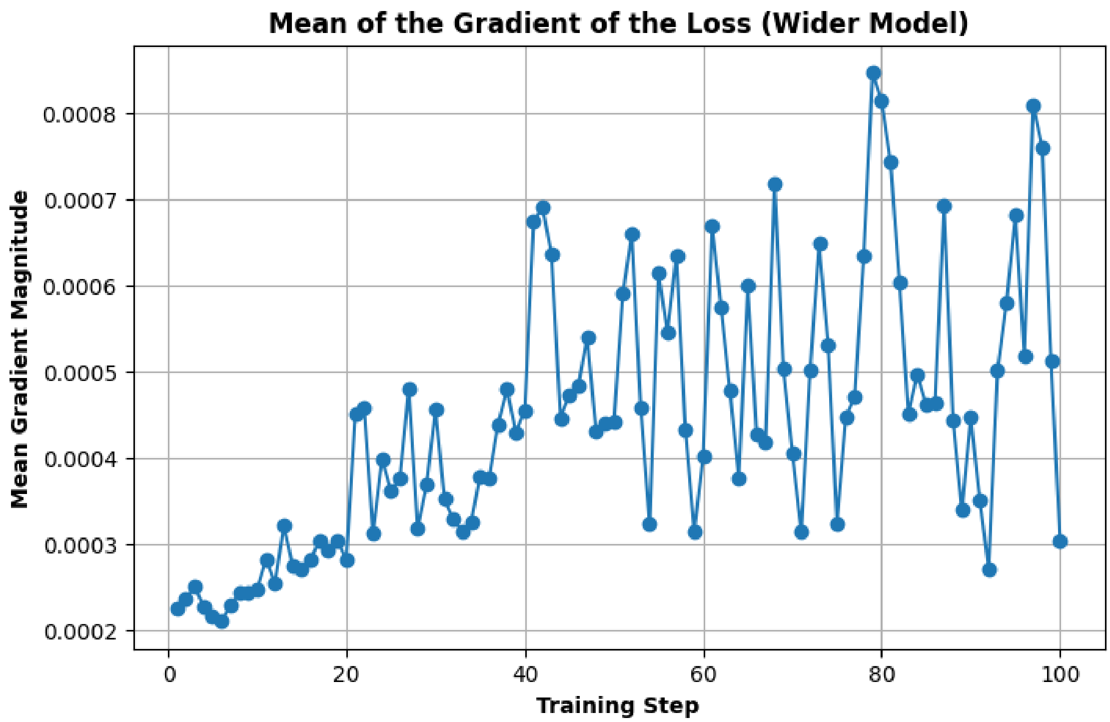
In contrast, the deeper model introduced two additional hidden layers, resulting in a total of five fully connected layers with 512 neurons each. This increased the parameter count to 830,090, which is more than the base model but still less than the wider one. Surprisingly, this configuration led to a slightly lower test accuracy than the wider model, achieving only 87.40% accuracy on average. The loss curve showed sharper fluctuations, and the accuracy curve was more erratic, indicating less stable convergence during validation. Deeper networks can suffer from issues such as vanishing gradients and optimisation difficulties, particularly when not paired with architectural enhancements like batch normalisation or residual connections. In this case, the added depth may have made it harder for the model to learn effectively, resulting in higher loss and only marginally better performance over the base model.

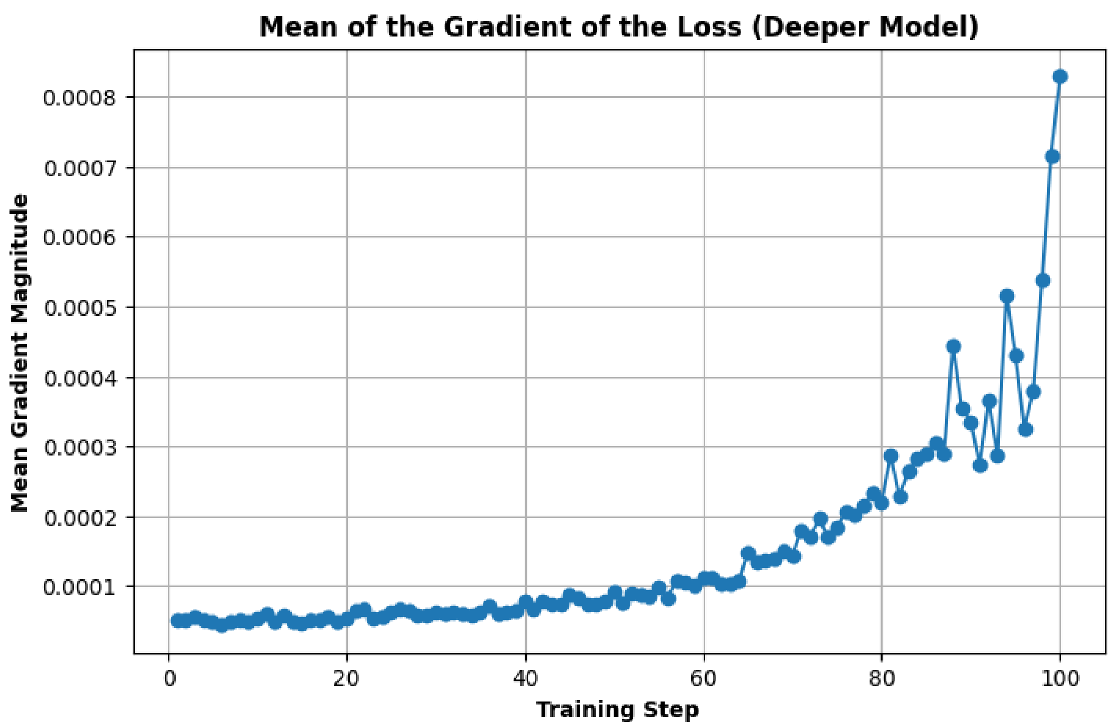
Overall, the experiments above demonstrate that widening the network can improve the training behaviour and enhance generalisation, while deepening the network makes training more unstable, but can result in performance improvments. These results suggest that for datasets like FashionMNIST, where the classification task is relatively straightforward, increasing model complexity beyond a certain point provides diminishing returns.

1.1.6 Q1.6 *(2 Points)*

Calculate the mean of the gradients of the loss to all trainable parameters. Plot the gradients curve for the first 100 training steps. What are your observations? Note that this gradients will be saved with the training weight automatically after you call loss.backwards(). **Hint:** The mean of the gradients decrease.




Mean of the Gradient of the Loss (Wider Model)
Mean Gradient Magnitude
Training Step
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0
20
40
60
80
100


Mean of the Gradient of the Loss (Deeper Model)
Mean Gradient Magnitude
Training Step
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
0.0007
0.0008
0
20
40
60
80
100

After computing and visualising the mean of the gradient of the loss with respect to all trainable parameters over the first 100 training steps, several noteworthy patterns emerge across different architectures. It is important to clarify that the gradient of the loss is not itself a loss value, and therefore it is not necessarily expected to decrease over time. Rather, observing the gradient of the loss helps to understand whether the model is still learning. If the gradients become too small *(vanishing)* or too large *(exploding)*, this could indicate training instability.

Interestingly, in the first 100 steps of training, the mean of the gradients of the loss often increases rather than decreases, which may seem counterintuitive. This occurs because, during early training, model parameters are still near their random initialisation and have not yet begun to meaningfully reduce the loss. Consequently, gradient magnitudes may grow as the model begins to adjust weights to capture learning signals.

In the base model *(smallest parameter count)*, gradients exhibit considerable oscillation between ~0.0003 and ~0.0012. This volatility likely stems from the model's limited capacity; each update causes a more pronounced shift in the output, leading to less stable gradient behaviour. In contrast, the wider model *(more neurons per layer)* shows fluctuations within a narrower range *(~0.0002 to ~0.0008)*. The increased number of neurons spreads the learning signal more evenly across parameters, resulting in smaller, more stable gradients.

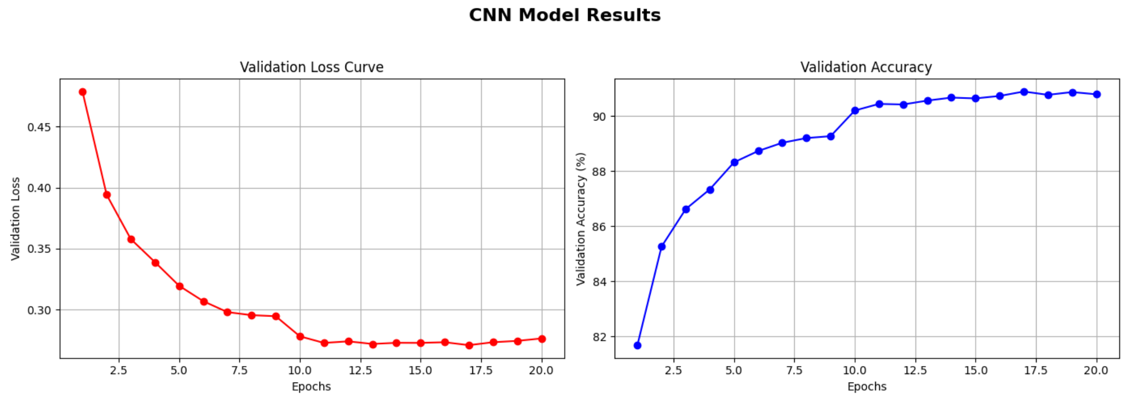
The deeper model, with additional hidden layers, starts with low gradient values *(~0.00005)* that steadily rise to ~0.0008. This may reflect early challenges in gradient propagation *(e.g. vanishing gradients)*, followed by a gradual improvement as the model begins learning more abstract representations, assuming appropriate weight initialisation and activations. Overall, these findings show that architecture has a significant impact on early gradient dynamics. Smaller models yield more erratic gradients, wider models benefit from more stable updates, and deeper models require time for gradients to propagate effectively. The key takeaway is that increasing gradients during early training is not inherently problematic; it often reflects the model beginning to learn.

1.1.7 Q1.7 *(5 Points)*

Modify the network structure and training/test to use a small convolutional neural network instead of an MLP. Discuss your findings with regard to convergence, accuracy and number of parameters, relative to MLPs. **Hint:** Look at the structure of the CNN in the Workshop 3 examples.

For more explanation of Q1.7, you could refer to the following simple instructions: https://colab.research.google.com/drive/1XAsyNegGSvMf3_B6MrsXht7-fHqtJ7OW?usp=sharing.

```
Trainable parameters: 20490
```



After training and analysing Multi-Layer Perceptron (MLP) models, a simple Convolutional Neural Network (CNN) was implemented and trained using a comparable learning rate *(0.1)*. The CNN architecture includes two convolutional layers followed by a fully connected output layer. Crucially, ReLU activation functions were applied after each convolutional layer to introduce non-linearity, which enables the model to learn complex, hierarchical feature representations from the input images. This non-linearity is a significant advantage of CNNs over traditional MLPs, as it allows the network to better capture spatial hierarchies in image data. Additionally, the CNN employs max pooling layers to progressively reduce spatial dimensions, which helps reduce the number of parameters and computational cost compared to a fully connected architecture. The results of this show several key differences that can be observed regarding convergence, accuracy, and parameter count.

The CNN model converged in approximately 13 epochs, whereas the best-performing MLP reached convergence in around 15 epochs. This difference in convergence speed can be attributed to the structural differences between the two architectures. Convolutional Neural Networks incorporate inductive biases such as spatial locality and translation invariance, which enable them to learn hierarchical representations of features from image data more efficiently. While convolution and pooling operations introduce additional computational steps, these mechanisms allow the CNN to extract meaningful patterns and reduce spatial dimensions progressively, facilitating faster convergence. The reduced number of training epochs reflects the model's ability to rapidly learn low to high-level features across its layers.

As well as taking less time to converge, the CNN achieved a higher accuracy of approximately 90.5% on average, compared to the best MLP *(~88%)*. This is expected because CNNs are inherently better at processing spatial data, like images. The use of convolutional layers allows the network to learn local patterns *(edges and textures)* and build up to more abstract features in deeper layers. Additionally, the incorporation of ReLU activation layers introduces non-linearity, enabling the model to learn more complex functions and improving its capacity to generalise to the data. In contrast, MLPs treat all input pixels equally and don't capture spatial relationships, which limits their performance on image classification tasks. This is why CNNs outperform MLPs even with fewer training parameters.

An interesting and important observation is that the CNN had only 20,490 trainable parameters, compared to 669,706 for the smallest MLP, a reduction of about 31.5x. This large difference is due to weight sharing in convolutional layers. In MLPs, every neuron in one layer is connected to every neuron in the next, resulting in a huge number of parameters. In CNNs, each filter is applied across the entire input image, dramatically reducing the number of weights while still allowing the network to extract relevant features. Pooling layers further reduce spatial dimensions, leading to a much more compact and accurate model.

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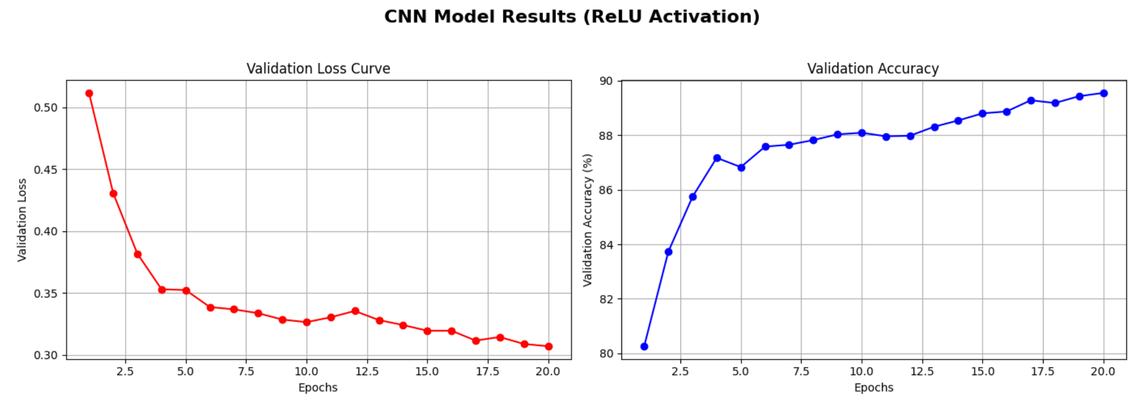
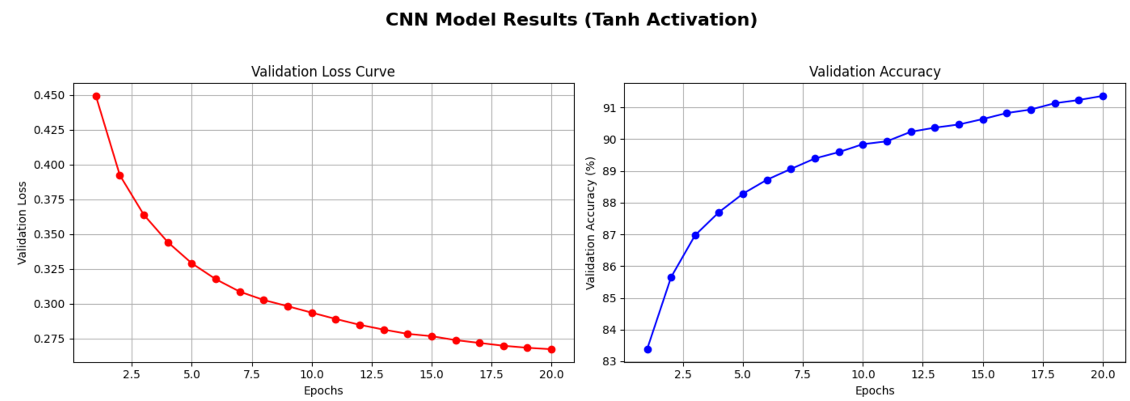
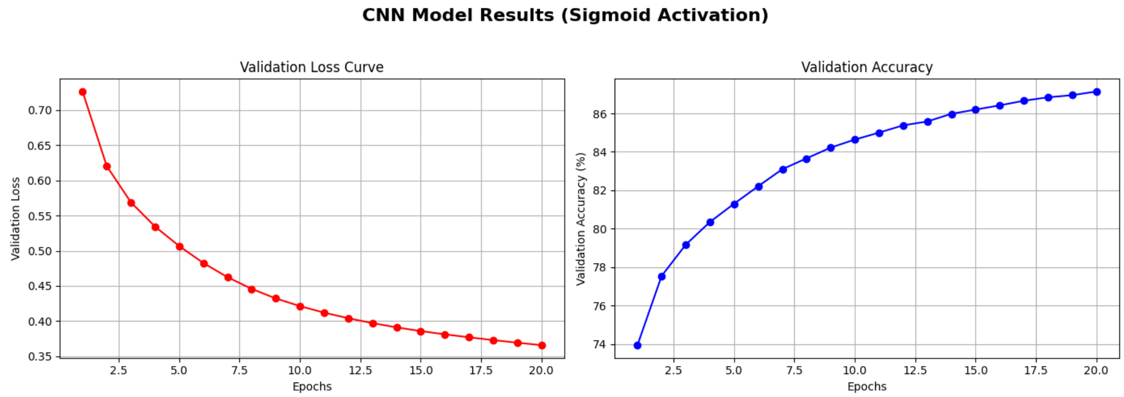
2 Question 2: Optional Bonus Question *(5 Marks, 20% Bonus Marks)*

2.0.1 Q2.1 *(2 Points)*

Experiment with different activation functions (ReLU, Tanh, Sigmoid) and analyse their impact on training performance.







Similar to the convolutional neural network (CNN) used in part 1.7, the model implemented above consists of two convolutional layers, each followed by an activation layer and a max-pooling operation, before passing through a fully connected linear layer. This structure was chosen for its balance between model complexity and interpretability, especially given the nature of the dataset. The first convolutional layer captures low-level features such as edges, while the second layer builds on these to detect more abstract patterns. By applying a padding of one in the convolutional layers, the spatial dimensions of the input are preserved, which helps retain information near the borders. Bias terms were included in each layer to increase the flexibility of the learned transformations, and the max-pooling operations serve to reduce the spatial resolution, encourage translational invariance, and decrease computational load.

The inclusion of activation functions is critical, as they introduce non-linearity, allowing the model to learn complex, real-world patterns that a purely linear system could not capture. ReLU (Rectified Linear Unit), Tanh, and Sigmoid functions were each tested to observe their impact on training behaviour and model performance. The training was conducted using a consistent number of epochs and learning rate across all three activation setups *(e.g. 20 epochs with a learning rate of 0.1)*, to ensure a fair comparison.

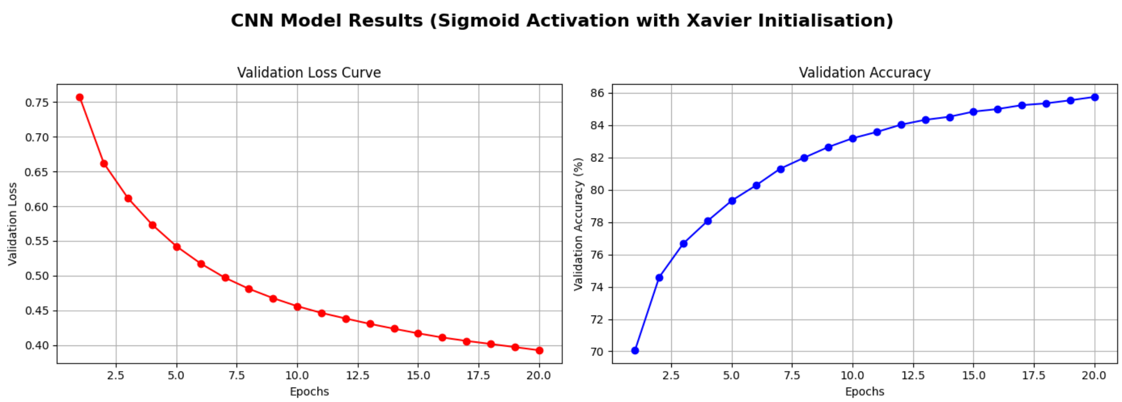
With ReLU, the model achieved approximately 90% accuracy on average when validated on the test dataset, a clear improvement over the baseline models used in question 1. Additionally, the validation loss decreased steadily and corrected itself effectively within the first few epochs. This behaviour is typical of ReLU due to its ability to maintain strong gradients and avoid saturation, enabling rapid and stable learning in the early stages.

Interestingly, the model using the Tanh activation function outperformed ReLU, achieving a test accuracy of approximately 91.5% on average. The loss curve was very smooth, indicating stable convergence throughout training. While Tanh generally performs best with zero-centred inputs, this result suggests that even without normalising the Fashion-MNIST dataset around zero *[-1,1]*, Tanh was able to effectively transform the positively skewed input values. This may be due to its non-linearity and ability to output both positive and negative values, which still supports a more balanced gradient flow compared to the Sigmoid activation function. Although ReLU is typically more robust to input scale, in this case, Tanh's smoother gradient across its range appears to have offered a slight advantage in convergence and final accuracy.

In contrast, the Sigmoid activation function led to slower learning and lower overall performance, with the model only reaching around 86.5% accuracy on average. The gradient was not as steep during the early epochs, and the model converged more slowly. This is a known limitation of the Sigmoid function, which tends to suffer from vanishing gradients as the output saturates for large input values. While preprocessing operations like Xavier initialisation may help mitigate this by keeping the signal variance stable across layers, the fundamental limitations of Sigmoid in deep networks mean it typically underperforms compared to ReLU or Tanh in this kind of setting.

2.0.2 Q2.2 *(1 Point)*

In particular, focus your analysis on the Sigmoid activation function and discuss your finding of training with and without Xavier initialisation. You may use the provided code for Xavier initialisation for this.

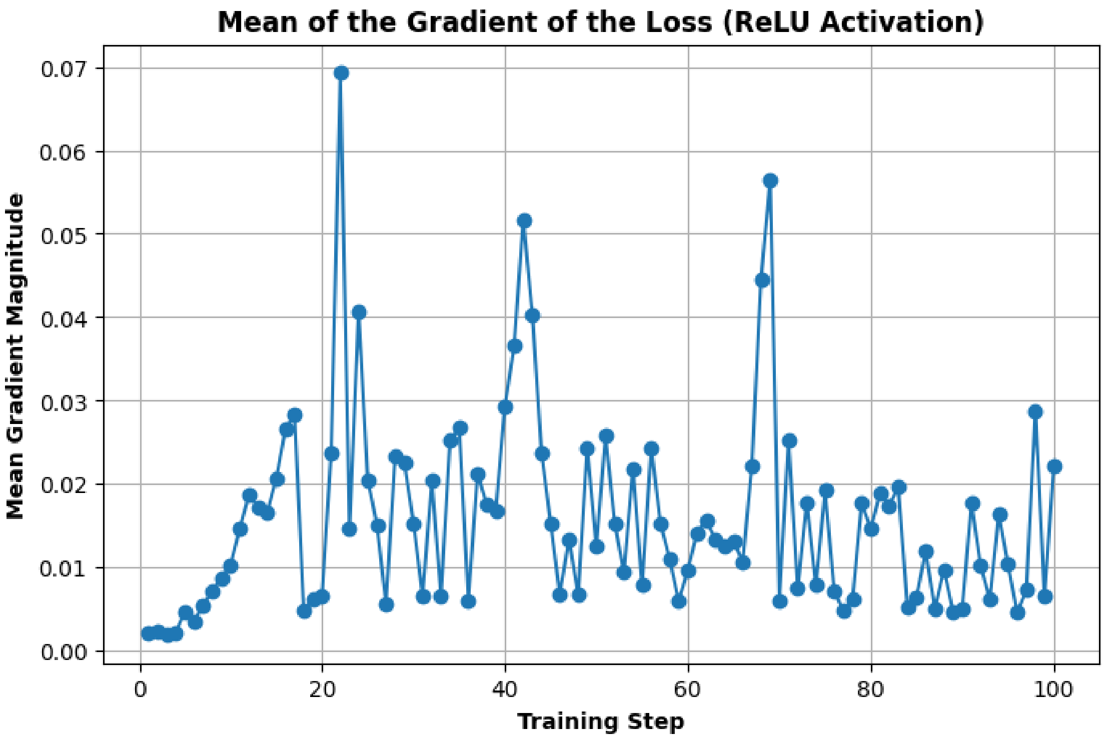


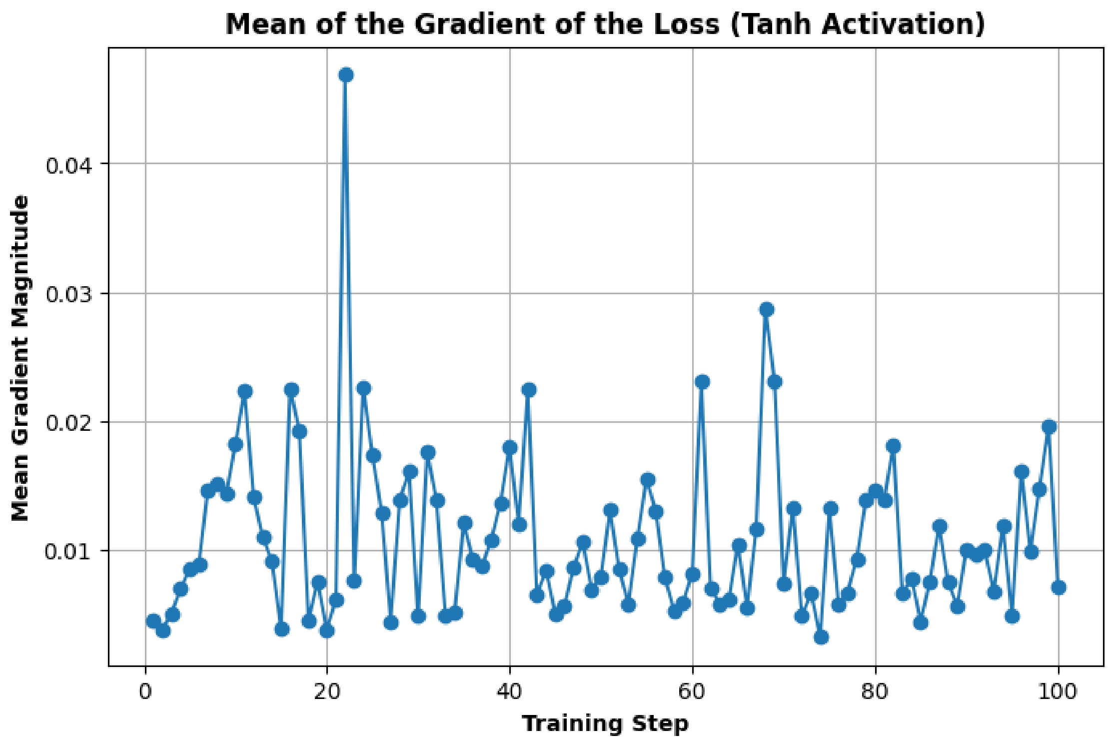
When using the Sigmoid activation function without any special weight initialisation, the model exhibited slow convergence and achieved a lower final accuracy *(approximately 86.5%)* compared to models using ReLU or Tanh. This is expected behaviour, as Sigmoid activations are known to suffer from vanishing gradients, especially when deeper in the network or when weights are poorly scaled. To try and improve the results for the Sigmoid Function, Xavier initialisation was applied in an attempt to mitigate this issue.

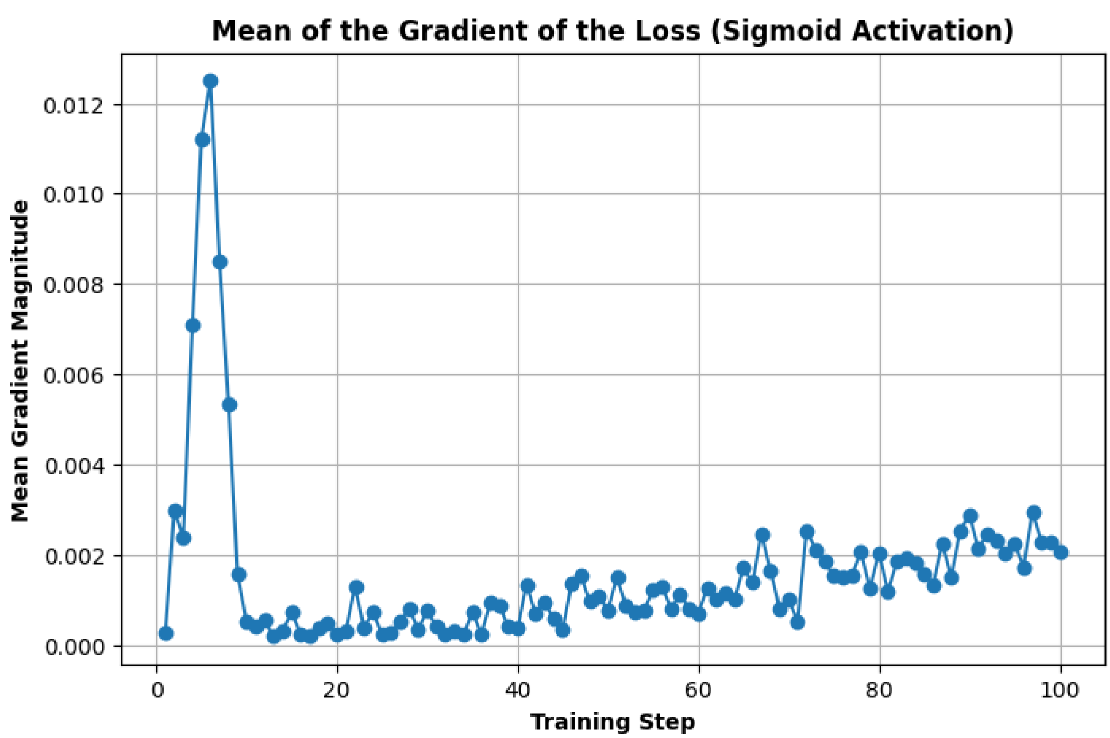
Theoretically, Xavier initialisation helps maintain stable gradients throughout training by scaling the initial weights based on the number of input and output connections, a method that works particularly well with symmetric activation functions like Sigmoid. However, in practice, the model using Sigmoid activation layers with Xavier initialisation actually performed about the same, achieving an accuracy of approximately 86% on average. One likely explanation is that the Fashion-MNIST dataset is relatively simple, and the network is shallow, so the benefits of careful weight scaling are less pronounced. In such cases, small variations due to weight initialisation may have a minor impact, and training instability due to suboptimal initialisation is unlikely to manifest significantly. Another possibility is that Sigmoid's intrinsic limitations *(such as saturation at extremes)* still hinder its learning dynamics, even with better-initialised weights.

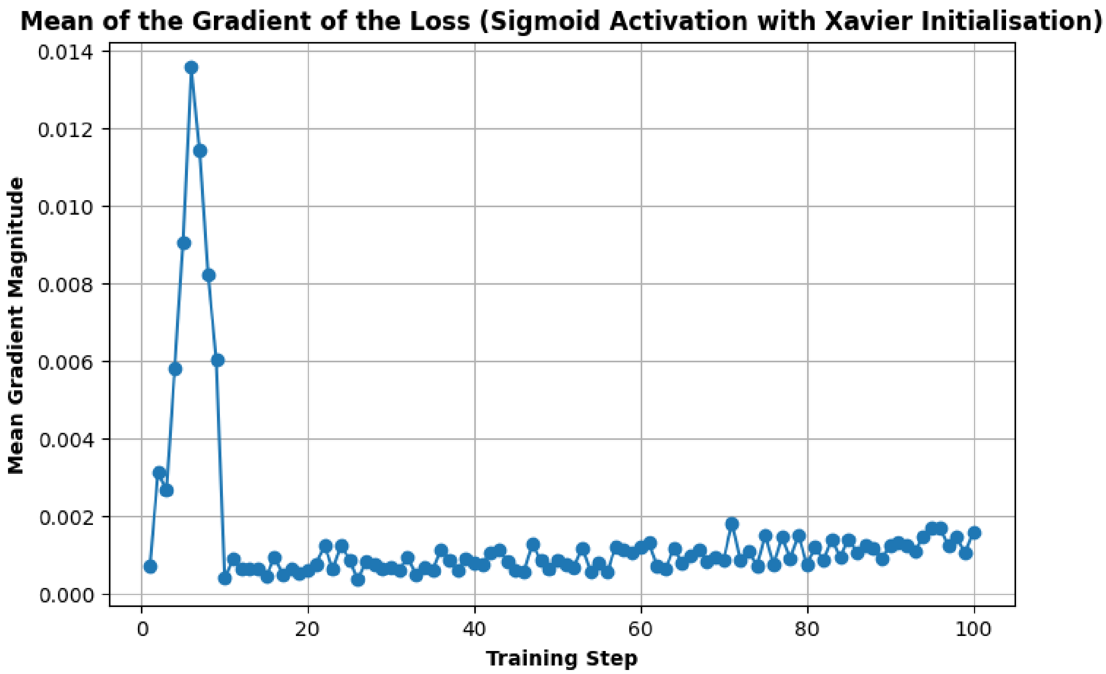
2.0.3 Q2.3 *(1 Point)*

Additionally, plot both the gradient and loss curves for your experiments. For gradient analysis, you may select one representative layer to monitor throughout training and briefly explain your choice.




Mean of the Gradient of the Loss (Tanh Activation)
Mean Gradient Magnitude
Training Step
0.01
0.02
0.03
0.04
0
20
40
60
80
100


Mean of the Gradient of the Loss (Sigmoid Activation)
Mean Gradient Magnitude
Training Step
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0
20
40
60
80
100



For this analysis, the first convolutional layer `conv1` was selected as the representative layer for monitoring gradients. This layer was chosen because it is directly impacted by the activation function and is close to the input. As a result, it provides a clear view of how well gradients are able to propagate backwards through the network. If vanishing gradients occur due to poor activation or initialisation, they are most likely to show up clearly in the earliest layers.

In the case of the **ReLU** activation function, the gradient values fluctuated within a moderate range *(approximately 0.005 to 0.03)*, with occasional sharp spikes reaching up to around 0.07. These spikes likely correspond to specific batches with more active neurons or large errors, causing stronger updates. ReLU is known for sparse activation, so neurons can *"die"* if they receive no gradient, but when active, they propagate strong gradients, which explains the sharp but infrequent spikes.

The **Tanh** activation showed smoother, less noisy gradient curves, typically oscillating between ~0.005 and ~0.02, with rare spikes reaching around 0.04. Tanh maintains a more consistent gradient due to its continuous and symmetric shape, resulting in more stable updates. Its zero-centred nature supports better gradient flow, which is why its gradient curve is more stable and controlled compared to ReLU.

The **Sigmoid** function demonstrated a very different pattern. It showed a large spike in the first few epochs *(from ~0.0002 to ~0.012)*, followed by a slower, steady increase in gradient values, eventually plateauing near 0.0035. This initial spike likely represents the network's attempt to push activations out of the saturated regions of the sigmoid function where gradients vanish. As training progresses, the gradients improve slightly, but their small scale overall suggests the model is still struggling to update weights effectively, contributing to slower learning and lower accuracy.

When **Xavier initialisation** was applied to the model with the Sigmoid activation, the initial gradient spike remained, but the overall gradient curve was less steep and more controlled. The gradients increased to around 0.013 early on but eventually decreased and stabilised around 0.002. This behaviour suggests that Xavier initialisation helped prevent exploding gradients, but it may have also dampened the model's ability to make strong corrections in the early epochs. This reduced aggressiveness in learning could explain why the sigmoid model with Xavier performed slightly worse than the one without it. In this case, the gradients were too cautious to recover quickly from the initial poor weight regions.

2.0.4 Q2.4 *(1 Point)*

Discuss how gradients and loss behave across the network for different activation functions and initialisation methods if you see any difference.

Across all experiments, the behaviour of gradients and loss during training varied notably with the choice of activation function and weight initialisation. ReLU produced strong, fluctuating gradients that enabled fast convergence and high accuracy, although its *"spiky"* pattern reflects its sparse activation nature. Tanh led to smoother, more stable gradients and slightly better performance, likely due to its symmetric and zero-centred output that supports more consistent learning dynamics. In contrast, Sigmoid exhibited vanishing gradients, especially early in training, leading to slower convergence and reduced accuracy. While Xavier initialisation partially mitigated this by stabilising weight scaling and tempering the gradient explosion risk, it ultimately did not fully overcome the intrinsic limitations of Sigmoid in deeper networks. These observations highlight the critical interplay between activation functions and initialisation strategies in maintaining effective gradient flow, ensuring fast convergence, and maximising model performance.
