Assignment 2 – Neural Networks

Advanced Machine Learning (BA-64061-001)

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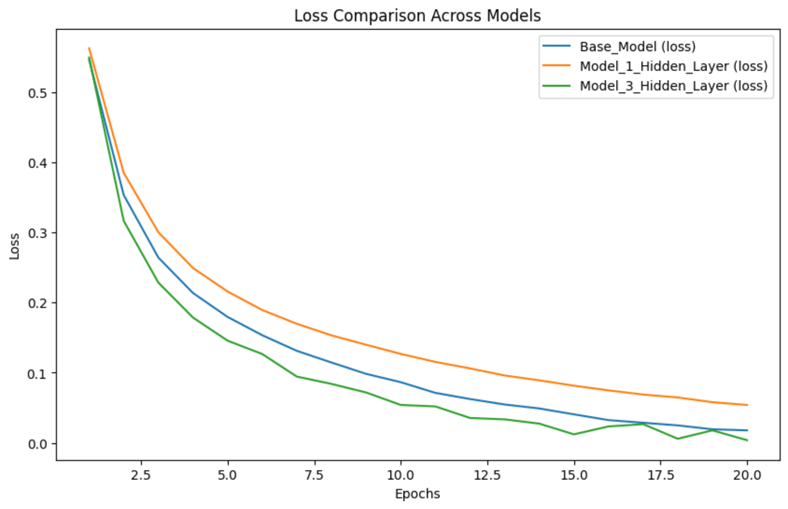
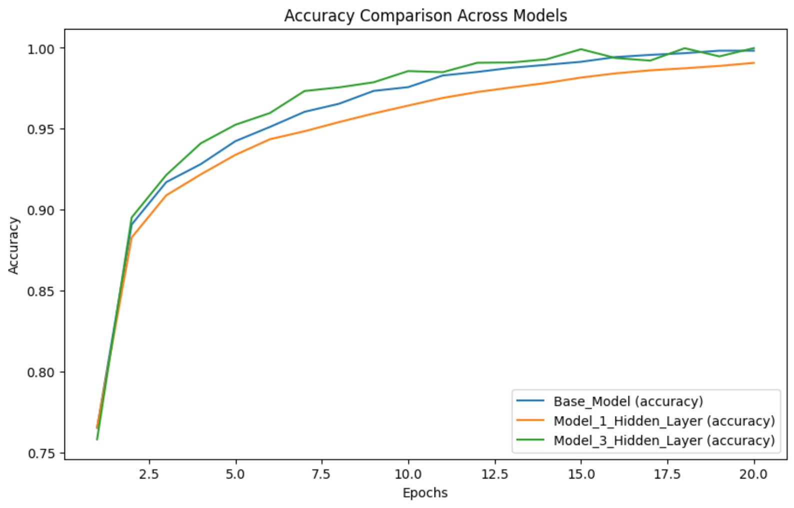
GitHub: Assignment 2 GitHub

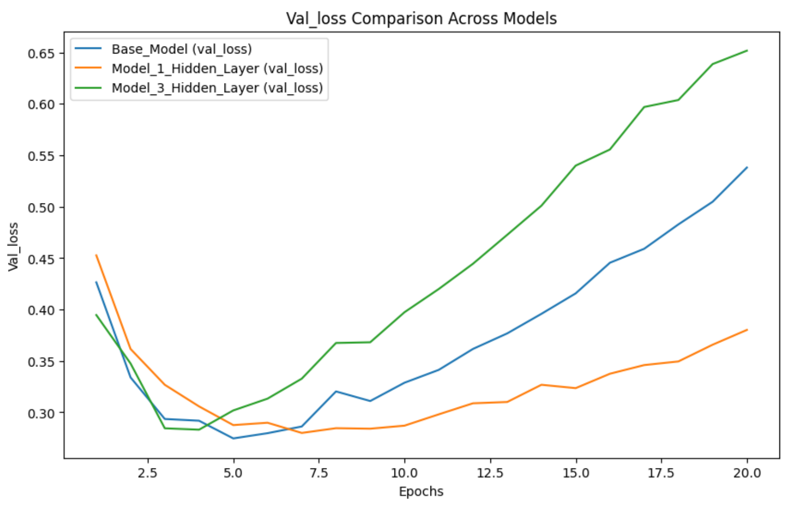
Q1. Comparing hidden layers with the base model.

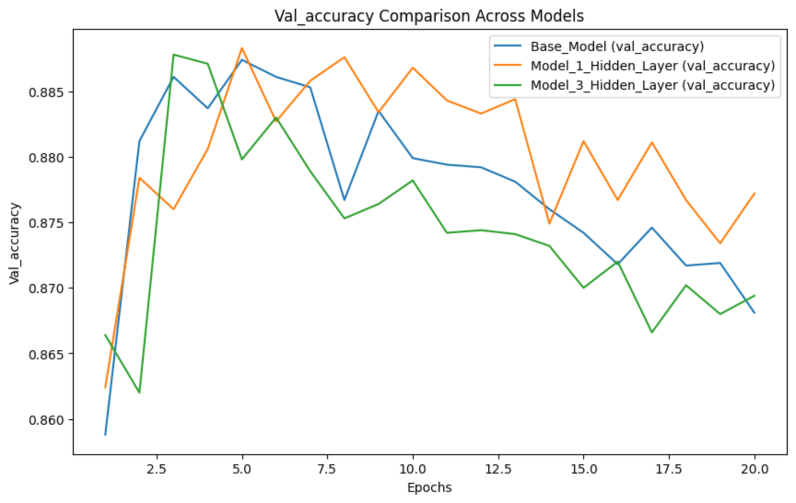
On comparing the hidden layers with the base model, we could find the following comparisons:

1. The base model with two hidden layers achieves the highest validation accuracy and the lowest loss, outperforming both the one-layer and three-layer models.
2. Model 1, which has a single hidden layer, demonstrates slightly lower validation and training accuracy than the base model.
3. Model 3, incorporating three hidden layers, does not enhance performance. Instead, it introduces instability, highlighting that adding more layers does not necessarily improve outcomes.
4. The base model with two hidden layers delivers the most balanced and optimal performance.



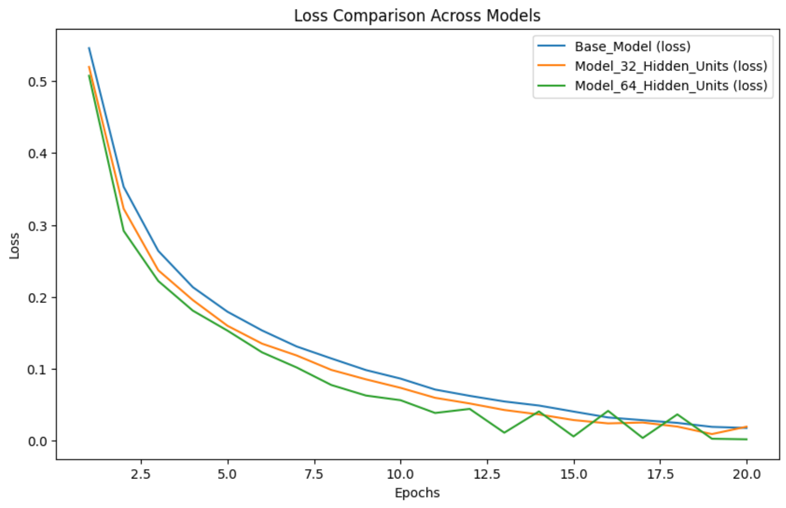


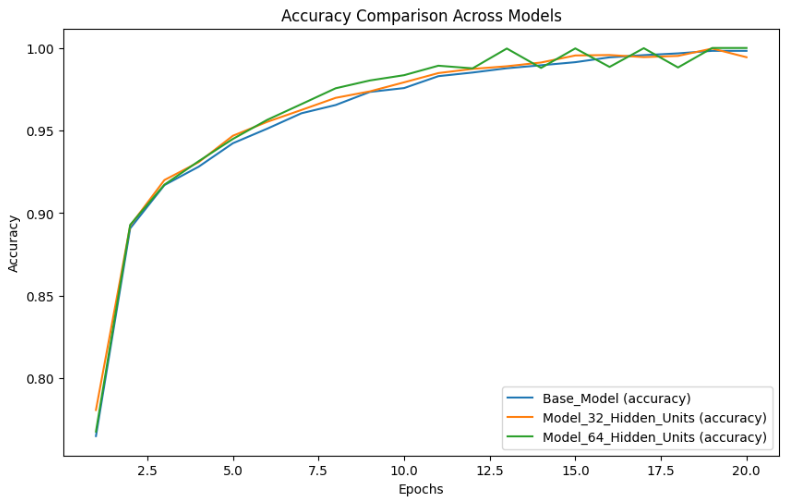


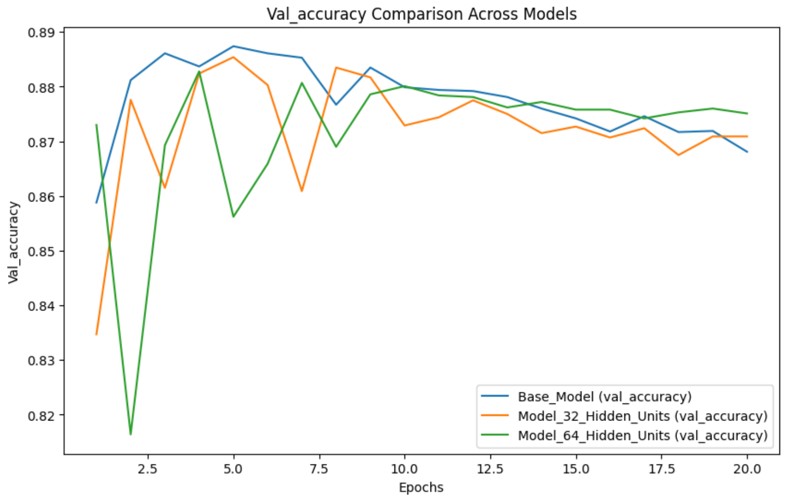


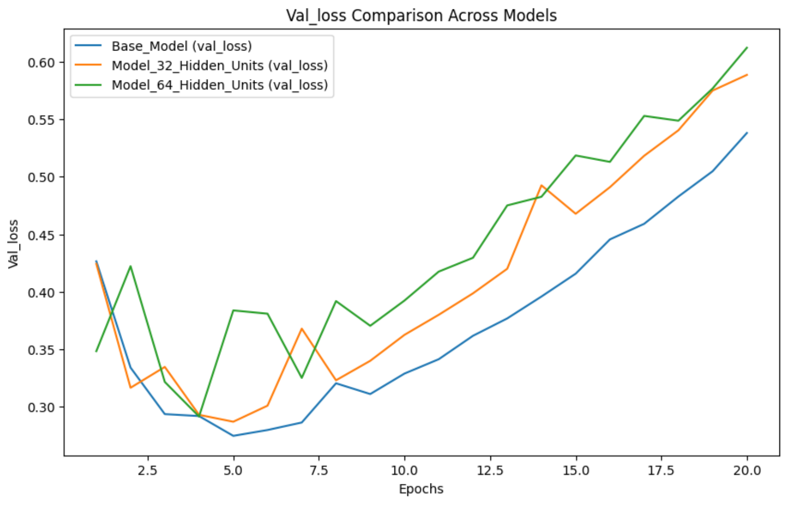
Q2. Comparing the base model with hidden unit values of 16,32 and 64.

1. In terms of validation accuracy, the model with 32 units outperforms those with 16 and 64 units. The model with 64 units exhibits lower and more fluctuating validation accuracy, whereas the 32-unit model performs similarly to the base model with 16 units.
2. The model with 64 hidden units achieves the lowest validation loss compared to the 32- and 16-unit models, particularly at higher epochs. This indicates that increasing the number of hidden units may contribute to overfitting and hinder generalization.
3. All models with 16, 32, and 64 units demonstrate comparable training accuracy and loss. However, the base model shows slightly better overall performance.
4. In conclusion, increasing the number of hidden units from 16 to 32 to 64 does not significantly enhance performance but introduces greater volatility, making the base model the more reliable choice.


Loss Comparison Across Models
Loss
Epochs
Base_Model (loss)
Model_32_Hidden_Units (loss)
Model_64_Hidden_Units (loss)

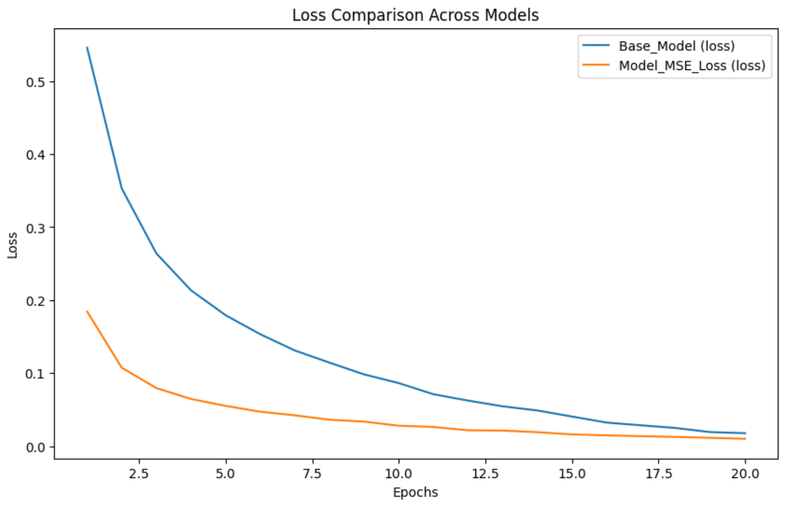

Accuracy Comparison Across Models
Accuracy
Epochs
Base_Model (accuracy)
Model_32_Hidden_Units (accuracy)
Model_64_Hidden_Units (accuracy)

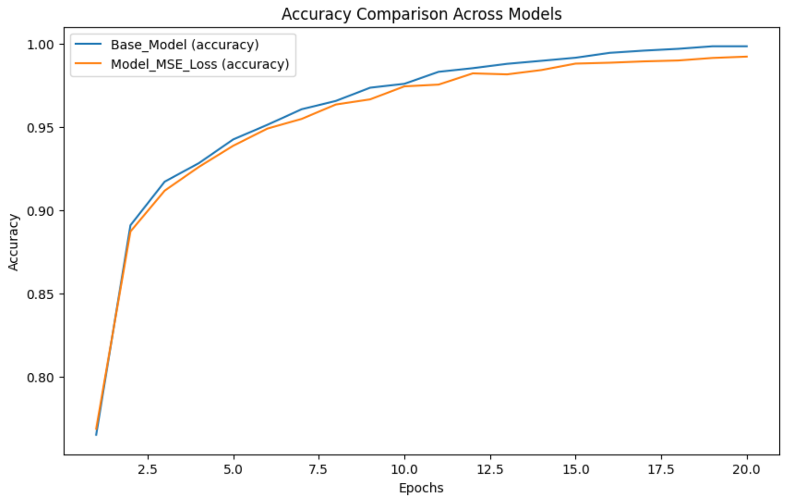

Val_accuracy Comparison Across Models
Val_accuracy
Epochs
Base_Model (val_accuracy)
Model_32_Hidden_Units (val_accuracy)
Model_64_Hidden_Units (val_accuracy)

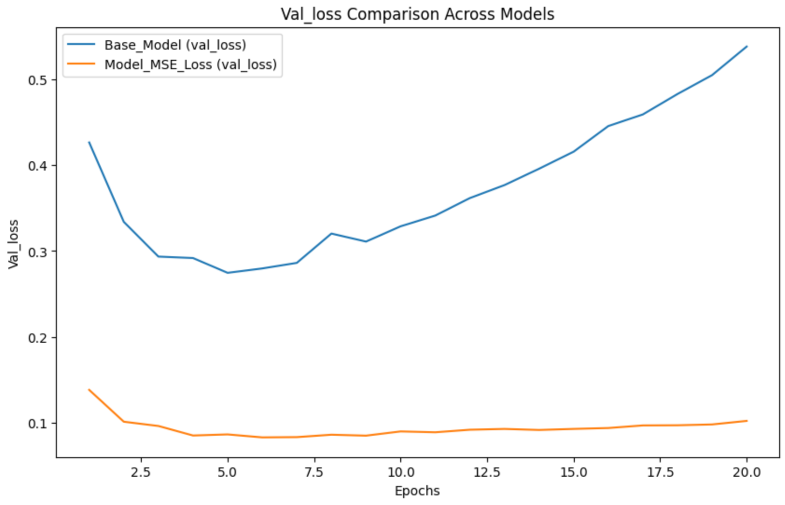


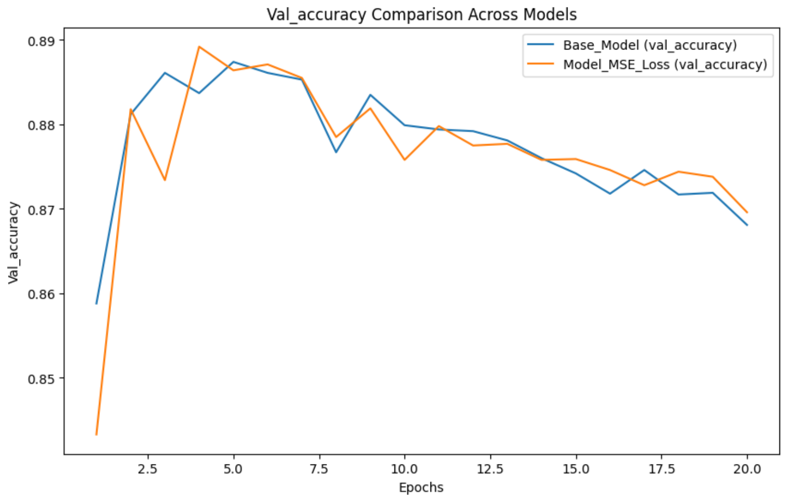
Q3. Try using the MSE loss functions instead of binary cross-entropy.

1. While Binary Cross-Entropy (BCE) is typically preferred for binary classification, Mean Squared Error (MSE) delivers significantly better performance in this case.
2. MSE excels in validation loss reduction, exhibiting a lower validation loss compared to the base model. This indicates that the MSE model minimizes the error between predicted and actual values more effectively.
3. The MSE model achieves better results with fewer training epochs, demonstrating greater efficiency.
4. In summary, for this specific model, MSE proves to be a superior choice over BCE.



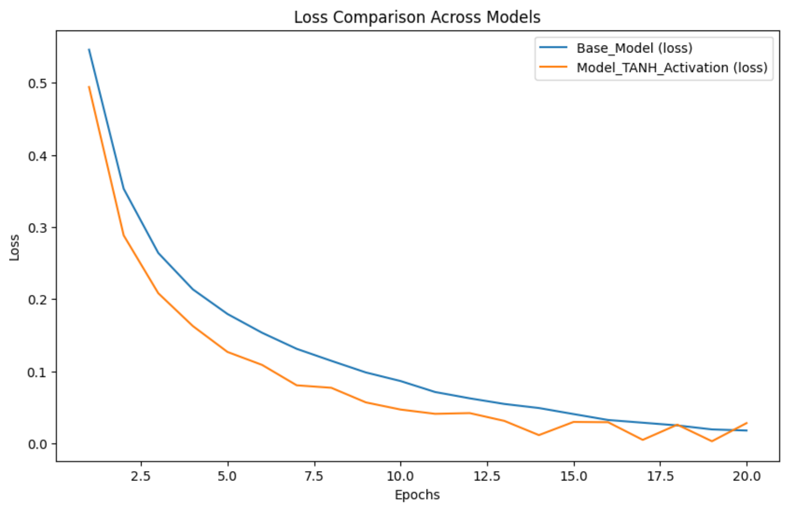

Accuracy Comparison Across Models
Base_Model (accuracy)
Model_MSE_Loss (accuracy)
Accuracy
Epochs
1.00
0.95
0.90
0.85
0.80
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

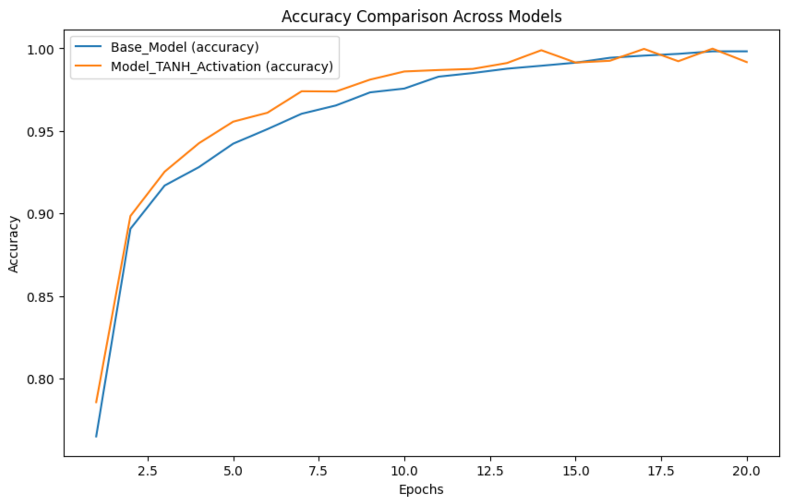

Val_loss Comparison Across Models
Base_Model (val_loss)
Model_MSE_Loss (val_loss)
Val_loss
Epochs
0.5
0.4
0.3
0.2
0.1
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

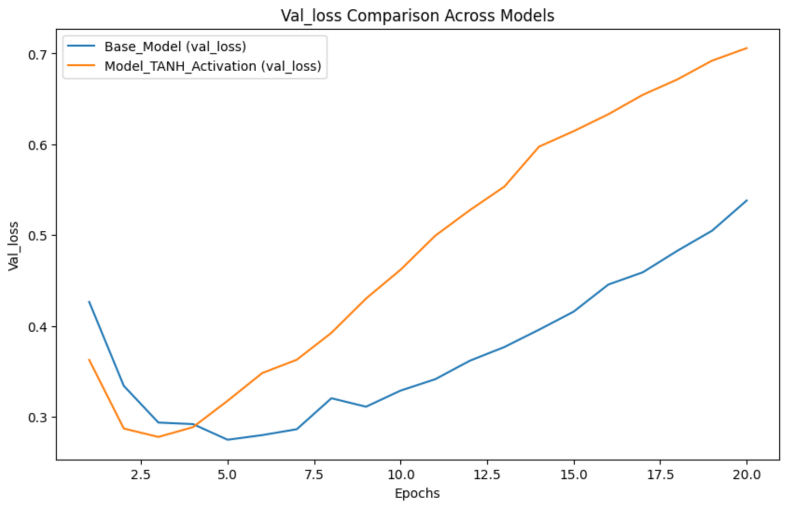

Val_accuracy Comparison Across Models
Base_Model (val_accuracy)
Model_MSE_Loss (val_accuracy)
Val_accuracy
Epochs
0.89
0.88
0.87
0.86
0.85
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

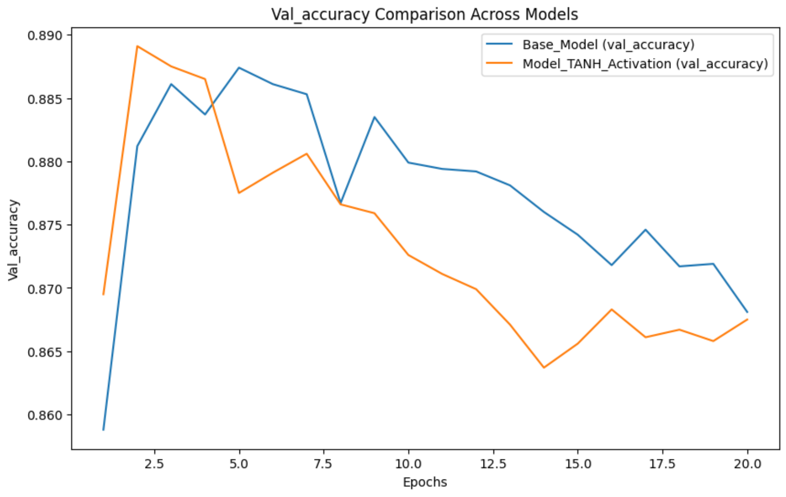
Q4. Comparing Tanh activation with the base model.

1. Experiment with the tanh activation function, which was widely used in the early days of neural networks, as an alternative to ReLU.
2. The ReLU activation (baseline model) outperforms Tanh, achieving higher accuracy.
3. The ReLU model also exhibits lower loss compared to the Tanh model, indicating that it more effectively minimizes the error between predicted and actual values.
4. In summary, ReLU proves to be the better choice, as it surpasses tanh in both accuracy and loss reduction.



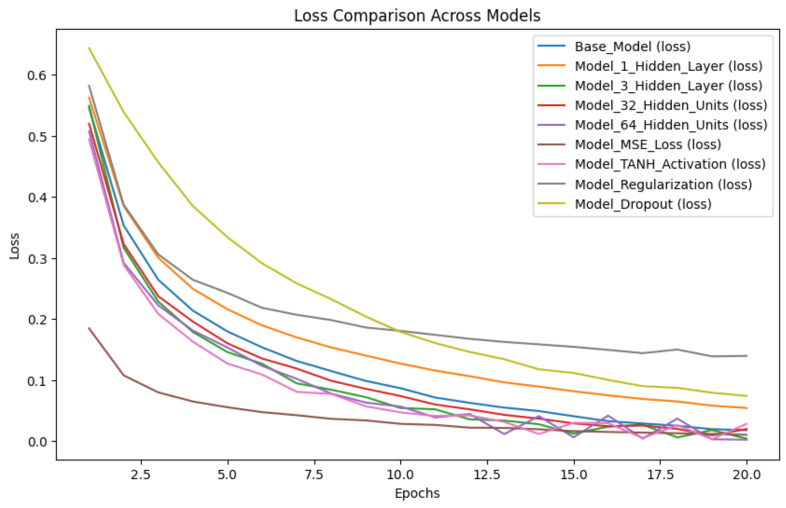


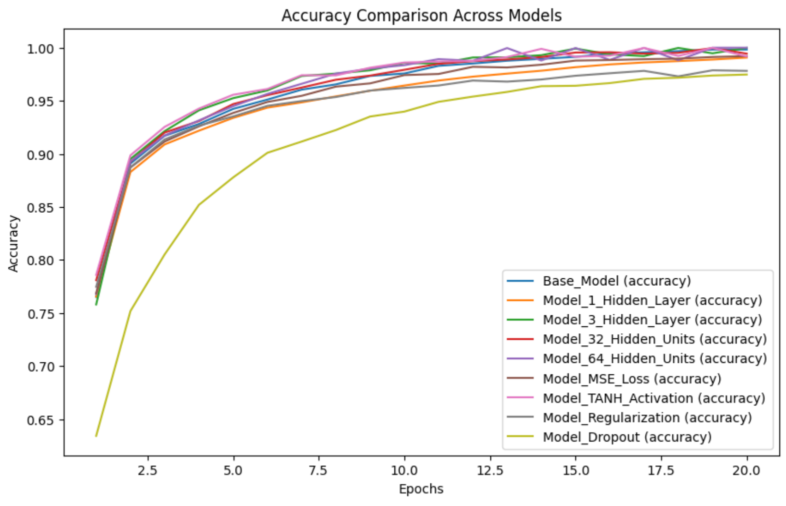


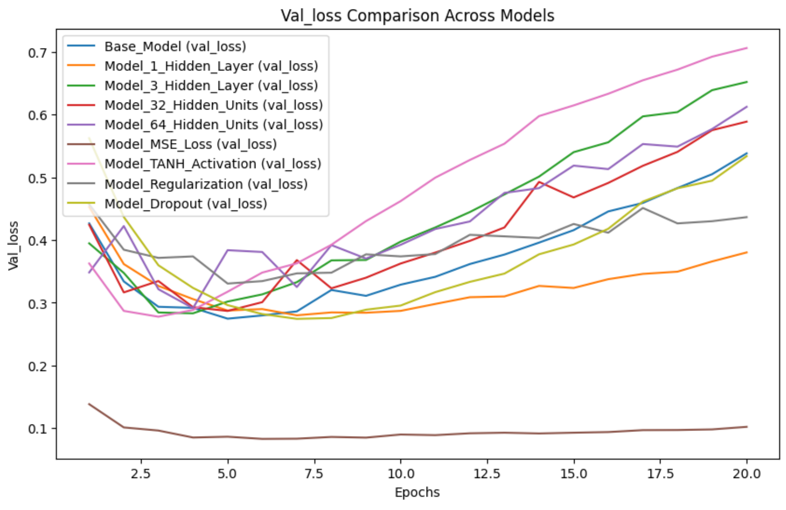


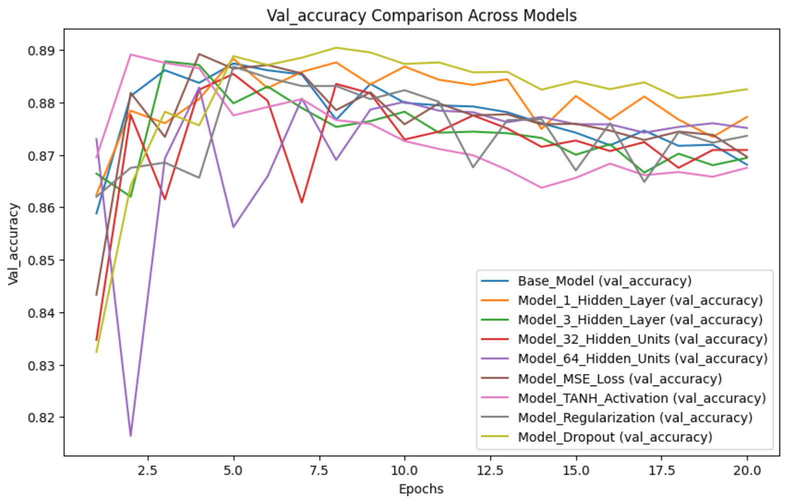
Q5. Comparison of L2 regularization, Dropout, and base model.

1. Used techniques such as regularization, dropout, or other optimization methods to enhance validation performance.
2. Dropout optimization achieves the highest accuracy compared to both the baseline model and L2 regularization.
3. In terms of loss reduction, dropout yields the lowest error rate, with L2 regularization closely following, while the baseline model proves less effective.
4. Based on performance across all metrics, dropout emerges as the most effective optimization technique for this model, outperforming both the baseline and L2 regularization.


Loss Comparison Across Models
Loss
Epochs
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Base_Model (loss)
Model_1_Hidden_Layer (loss)
Model_3_Hidden_Layer (loss)
Model_32_Hidden_Units (loss)
Model_64_Hidden_Units (loss)
Model_MSE_Loss (loss)
Model_TANH_Activation (loss)
Model_Regularization (loss)
Model_Dropout (loss)


Accuracy Comparison Across Models
Accuracy
Epochs
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Base_Model (accuracy)
Model_1_Hidden_Layer (accuracy)
Model_3_Hidden_Layer (accuracy)
Model_32_Hidden_Units (accuracy)
Model_64_Hidden_Units (accuracy)
Model_MSE_Loss (accuracy)
Model_TANH_Activation (accuracy)
Model_Regularization (accuracy)
Model_Dropout (accuracy)


Val_loss Comparison Across Models
Val_loss
Epochs
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Base_Model (val_loss)
Model_1_Hidden_Layer (val_loss)
Model_3_Hidden_Layer (val_loss)
Model_32_Hidden_Units (val_loss)
Model_64_Hidden_Units (val_loss)
Model_MSE_Loss (val_loss)
Model_TANH_Activation (val_loss)
Model_Regularization (val_loss)
Model_Dropout (val_loss)



Model	**Test Loss**	**Test Accuracy**
Base Model	0.29	0.88
1HL	0.28	0.88
3HL	0.37	0.87
32HU	0.29	0.88
64HU	0.30	0.89
MSE	0.09	0.88
Tanh	0.29	0.87
L2	0.34	0.88
Dropout	0.32	0.88

Note: Below are the snippets of code that are being attached. I printed the code from Google Collab because it was too large to take screenshots and attach them to the report. Only the code section is highlighted; the report summary is already provided above.

Loading the IMDB dataset

```
from tensorflow.keras.datasets import imdb
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(
    num_words=10000)
```

```
train_data[0]
```

Show hidden output

```
train_labels[0]
```

```
1
```

```
max([max(sequence) for sequence in train_data])
```

```
9999
```

Decoding reviews to text

```
word_index = imdb.get_word_index()
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])
decoded_review = " ".join(
    [reverse_word_index.get(i - 3, "?") for i in train_data[0]])
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb_word_index.json
1641221/1641221 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

Preparing the data

Encoding the integer sequences via multi-hot encoding

```
import numpy as np
def vectorize_sequences(sequences, dimension=10000):
    result = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        for j in sequence:
            result[i, j] = 1.
    return result
x_train = vectorize_sequences(train_data)
x_test = vectorize_sequences(test_data)
```

```
x_train[0]
```

```
array([0., 1., 1., ..., 0., 0., 0.])
```

```
y_train = np.asarray(train_labels).astype("float32")
y_test = np.asarray(test_labels).astype("float32")
```

Building the model different configurations

0. Model given by professor - Base point (model)

```
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

1. (Question 1) Building the model with 1 hidden layer (model_1_HL)

```
from tensorflow import keras
from tensorflow.keras import layers

model_1_HL = keras.Sequential([
    layers.Dense(16, activation="relu"), # Building the model with 1 hidden layer
    layers.Dense(1, activation="sigmoid")
])

model_1_HL.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

2. (Question 1) Building the model with 3 hidden layer (model_3_hl)

```
from tensorflow import keras
from tensorflow.keras import layers

model_3_HL = keras.Sequential([
    layers.Dense(16, activation="relu"), # hidden layer 1
    layers.Dense(16, activation="relu"), # hidden layer 2
    layers.Dense(16, activation="relu"), # hidden layer 3
    layers.Dense(1, activation="sigmoid")
])

model_3_HL.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

3. (Question 2) Building the model with fewer hidden units 32 (model_32_HU)

```
from tensorflow import keras
from tensorflow.keras import layers

model_32_HU = keras.Sequential([
    layers.Dense(32, activation="relu"), # hidden units 32
    layers.Dense(32, activation="relu"), # hidden units 32
    layers.Dense(1, activation="sigmoid")
    ])

model_32_HU.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

4. (Question 2) Building the model with higher hidden units 64 (model64_HU)

```
from tensorflow import keras
from tensorflow.keras import layers

model_64_HU = keras.Sequential([
    layers.Dense(64, activation="relu"), # hidden units 64
    layers.Dense(64, activation="relu"), # hidden units 64
    layers.Dense(1, activation="sigmoid")
    ])

model_64_HU.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

5. (Question 3) Building the base model with mse loss function (model_mse)

```
from tensorflow import keras
from tensorflow.keras import layers

model_mse = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])

model_mse.compile(optimizer="rmsprop",
              loss="mse",
              metrics=["accuracy"])
```

6. (Question 4) Building the model with tanh activation

```
model_tanh = keras.Sequential([
    layers.Dense(16, activation="tanh"), # tanh activation
    layers.Dense(16, activation="tanh"), # tanh activation
    layers.Dense(1, activation="sigmoid")
])

model_tanh.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

7. (Question 5) Building the model with regularization (model_reg)

```
from tensorflow.keras import regularizers

model_reg = keras.Sequential([
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common ac
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common ac
    layers.Dense(1, activation="sigmoid")
])

model_reg.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

8. (Question 5) Building the model with dropout (model_drp)

```
model_drp = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(1, activation="sigmoid")
])

model_drp.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

Creating a validation set

```
x_val = x_train[:10000]
partial_x_train = x_train[10000:]
y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

Training your model

0. Base model

```
Base_model = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

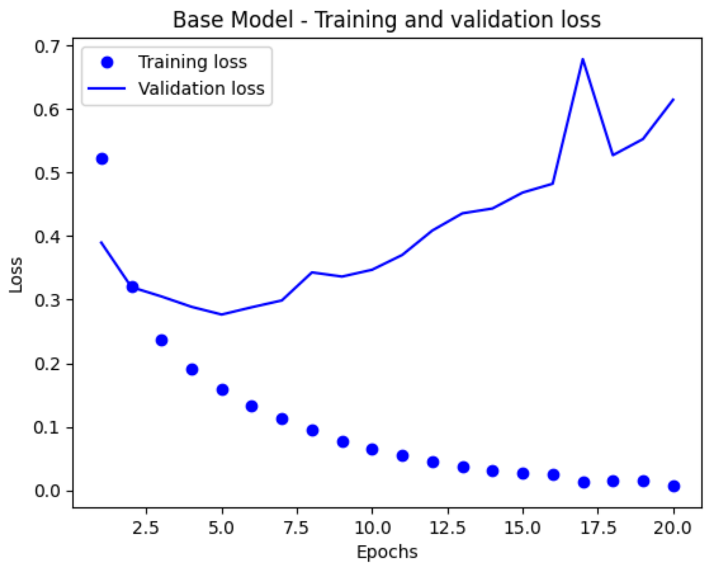
Show hidden output

```
Base_model_dict = Base_model.history
Base_model_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

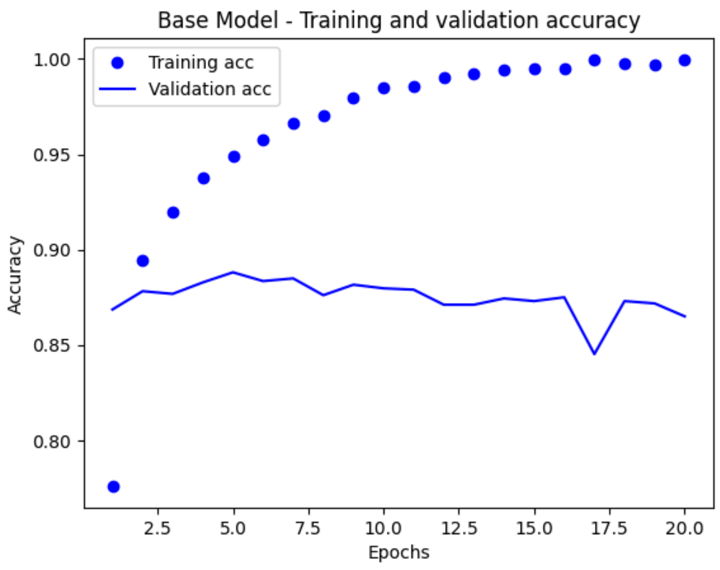
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Base_model_dict = Base_model.history
loss_values_0 = Base_model_dict["loss"]
val_loss_values_0 = Base_model_dict["val_loss"]
epochs = range(1, len(loss_values_0) + 1)
plt.plot(epochs, loss_values_0, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_0, "b", label="Validation loss")
plt.title("Base Model - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_0 = Base_model_dict["accuracy"]
val_acc_0 = Base_model_dict["val_accuracy"]
plt.plot(epochs, acc_0, "bo", label="Training acc")
plt.plot(epochs, val_acc_0, "b", label="Validation acc")
plt.title("Base Model - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model.fit(x_train, y_train, epochs=4, batch_size=512)
Base_model_results = model.evaluate(x_test, y_test)
```

Show hidden output

```
Base_model_results
```

```
[0.28912267088890076, 0.8853200078010559]
```

Using Trained data to predict

```
model.predict(x_test)
```

Show hidden output

1. Model With 1 Hidden Layer

```
Model_1_Hidden_Layer = model_1_HL.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

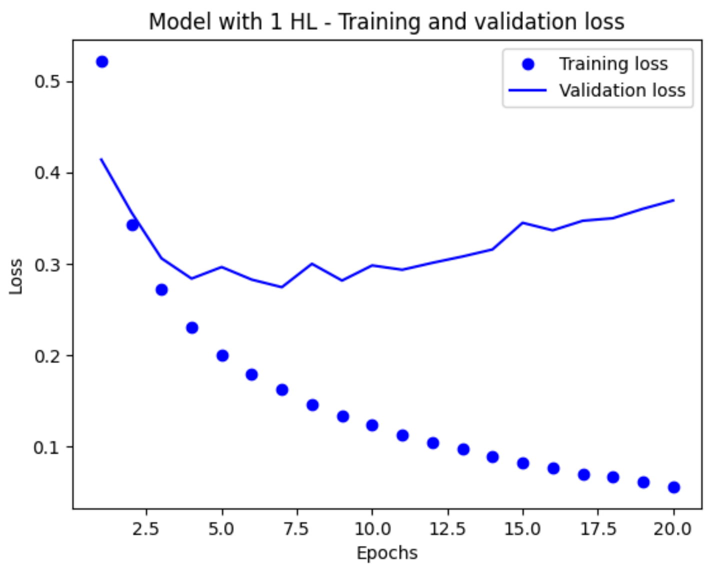
Show hidden output

```
Model_1_Hidden_Layer_dict = Model_1_Hidden_Layer.history
Model_1_Hidden_Layer_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

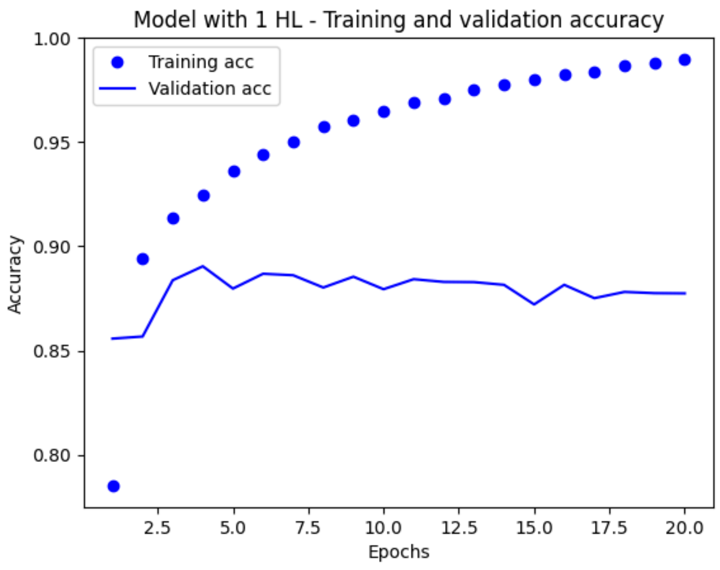
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_1_Hidden_Layer_dict = Model_1_Hidden_Layer.history
loss_values_1 = Model_1_Hidden_Layer_dict["loss"]
val_loss_values_1 = Model_1_Hidden_Layer_dict["val_loss"]
epochs = range(1, len(loss_values_1) + 1)
plt.plot(epochs, loss_values_1, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_1, "b", label="Validation loss")
plt.title("Model with 1 HL - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_1 = Model_1_Hidden_Layer_dict["accuracy"]
val_acc_1 = Model_1_Hidden_Layer_dict["val_accuracy"]
plt.plot(epochs, acc_1, "bo", label="Training acc")
plt.plot(epochs, val_acc_1, "b", label="Validation acc")
plt.title("Model with 1 HL - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_1_HL = keras.Sequential([
    layers.Dense(16, activation="relu"), # 1 Hidden Layer
    layers.Dense(1, activation="sigmoid")
])
model_1_HL.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_1_HL.fit(x_train, y_train, epochs=4, batch_size=512)
Model_1_Hidden_Layer_Results = model_1_HL.evaluate(x_test, y_test)
```

Show hidden output

```
Model_1_Hidden_Layer_Results
```

```
[0.2789919972419739, 0.8875200152397156]
```

Using Trained data to predict

```
model_1_HL.predict(x_test)
```

Show hidden output

2. Model With 3 Hidden Layer

```
Model_3_Hidden_Layer = model_3_HL.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

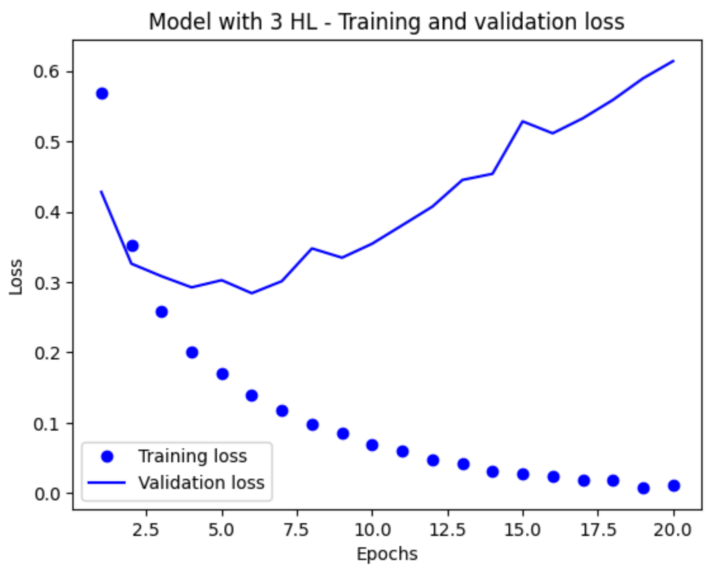
Show hidden output

```
Model_3_Hidden_Layer_dict = Model_3_Hidden_Layer.history
Model_3_Hidden_Layer_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

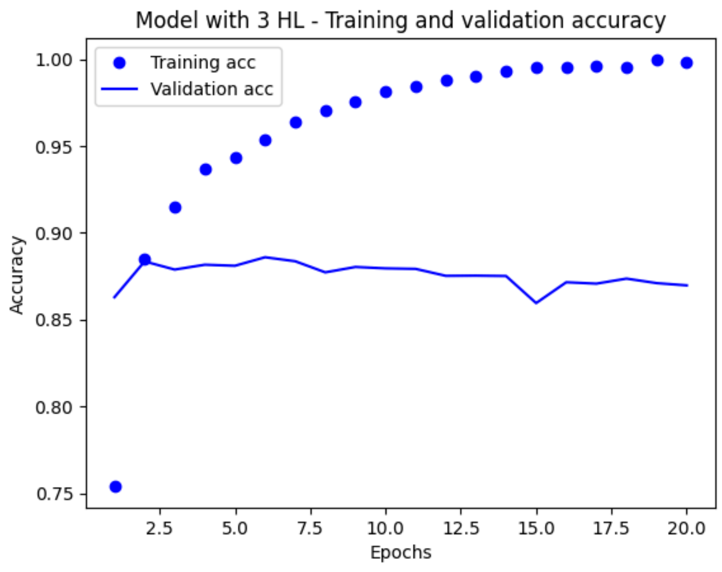
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_3_Hidden_Layer_dict = Model_3_Hidden_Layer.history
loss_values_3 = Model_3_Hidden_Layer_dict["loss"]
val_loss_values_3 = Model_3_Hidden_Layer_dict["val_loss"]
epochs = range(1, len(loss_values_3) + 1)
plt.plot(epochs, loss_values_3, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_3, "b", label="Validation loss")
plt.title("Model with 3 HL - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_3 = Model_3_Hidden_Layer_dict["accuracy"]
val_acc_3 = Model_3_Hidden_Layer_dict["val_accuracy"]
plt.plot(epochs, acc_3, "bo", label="Training acc")
plt.plot(epochs, val_acc_3, "b", label="Validation acc")
plt.title("Model with 3 HL - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_3_HL = keras.Sequential([
    layers.Dense(16, activation="relu"), # 1 Hidden Layer
    layers.Dense(16, activation="relu"), # 2 Hidden Layer
    layers.Dense(16, activation="relu"), # 3 Hidden Layer
    layers.Dense(1, activation="sigmoid")
])
model_3_HL.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_3_HL.fit(x_train, y_train, epochs=6, batch_size=512) # Epochs selected 6 because it starts to dip from 7
Model_3_Hidden_Layer_Results = model_3_HL.evaluate(x_test, y_test)
```

Show hidden output

```
Model_3_Hidden_Layer_Results
```

```
[0.320931613445282, 0.8784800171852112]
```

Using Trained data to predict

```
model_3_HL.predict(x_test)
```

Show hidden output

3. Model With 32 Hidden Units

```
Model_32_Hidden_Units = model_32_HU.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

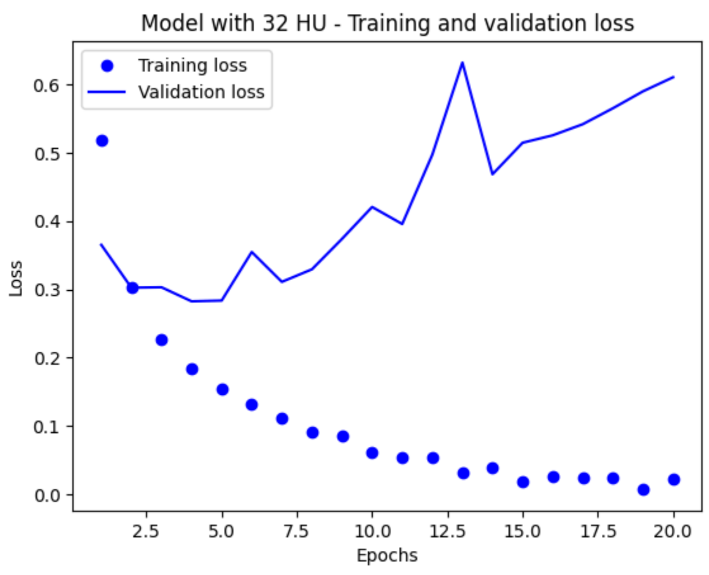
Show hidden output

```
Model_32_Hidden_Units_dict = Model_32_Hidden_Units.history
Model_32_Hidden_Units_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

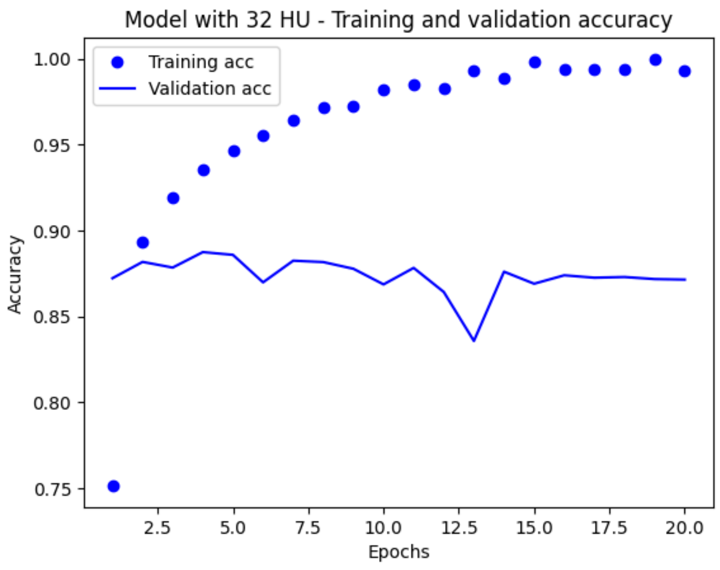
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_32_Hidden_Units_dict = Model_32_Hidden_Units.history
loss_values_32 = Model_32_Hidden_Units_dict["loss"]
val_loss_values_32 = Model_32_Hidden_Units_dict["val_loss"]
epochs = range(1, len(loss_values_32) + 1)
plt.plot(epochs, loss_values_32, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_32, "b", label="Validation loss")
plt.title("Model with 32 HU - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_32 = Model_32_Hidden_Units_dict["accuracy"]
val_acc_32 = Model_32_Hidden_Units_dict["val_accuracy"]
plt.plot(epochs, acc_32, "bo", label="Training acc")
plt.plot(epochs, val_acc_32, "b", label="Validation acc")
plt.title("Model with 32 HU - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_32_HU = keras.Sequential([
    layers.Dense(32, activation="relu"), # 32 Hidden Units
    layers.Dense(32, activation="relu"), # 32 Hidden Units
    layers.Dense(1, activation="sigmoid")
])
model_32_HU.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_32_HU.fit(x_train, y_train, epochs=3, batch_size=512) # Epochs selected 3 because it starts to dip from 3
Model_32_Hidden_Units_Results = model_32_HU.evaluate(x_test, y_test)
```

Show hidden output

```
Model_32_Hidden_Units_Results
```

```
[0.3259570300579071, 0.8698800206184387]
```

Using Trained data to predict

```
model_32_HU.predict(x_test)
```

Show hidden output

4. Model With 64 Hidden Units

```
Model_64_Hidden_Units = model_64_HU.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

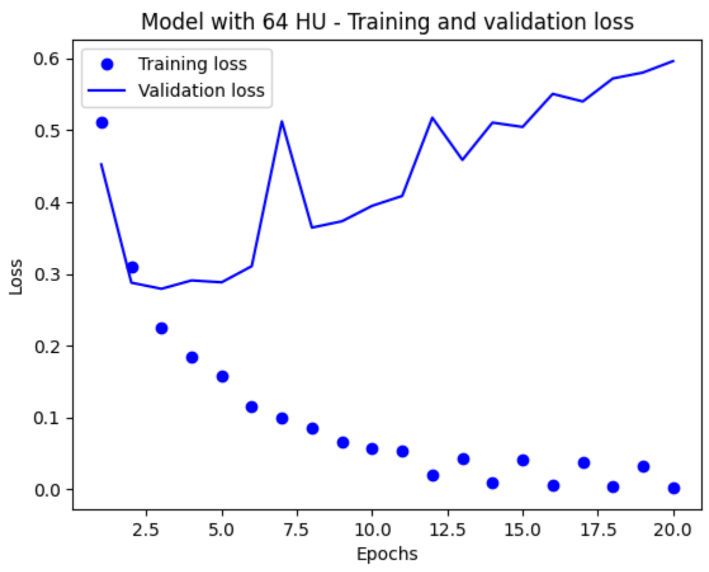
Show hidden output

```
Model_64_Hidden_Units_dict = Model_64_Hidden_Units.history
Model_64_Hidden_Units_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

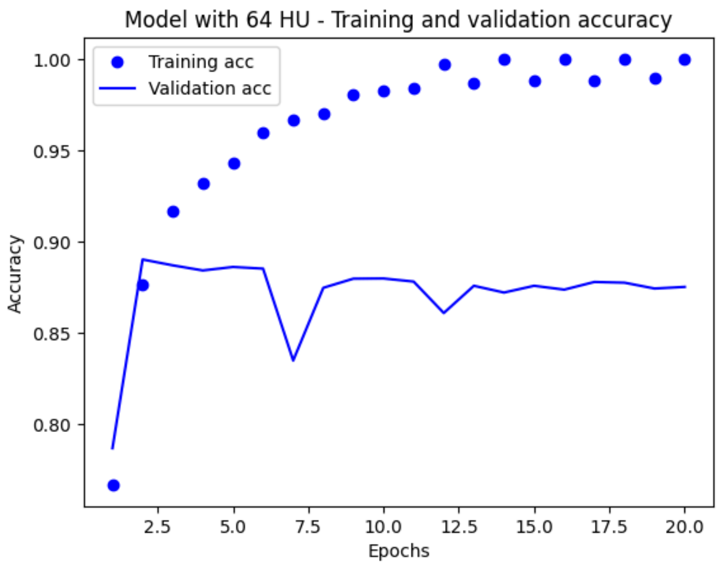
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_64_Hidden_Units_dict = Model_64_Hidden_Units.history
loss_values_64 = Model_64_Hidden_Units_dict["loss"]
val_loss_values_64 = Model_64_Hidden_Units_dict["val_loss"]
epochs = range(1, len(loss_values_64) + 1)
plt.plot(epochs, loss_values_64, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_64, "b", label="Validation loss")
plt.title("Model with 64 HU - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_64 = Model_64_Hidden_Units_dict["accuracy"]
val_acc_64 = Model_64_Hidden_Units_dict["val_accuracy"]
plt.plot(epochs, acc_64, "bo", label="Training acc")
plt.plot(epochs, val_acc_64, "b", label="Validation acc")
plt.title("Model with 64 HU - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_64_HU = keras.Sequential([
    layers.Dense(64, activation="relu"), # 64 Hidden Units
    layers.Dense(64, activation="relu"), # 64 Hidden Units
    layers.Dense(1, activation="sigmoid")
])
model_64_HU.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_64_HU.fit(x_train, y_train, epochs=2, batch_size=512) # Epochs selected 2 because it starts to dip from 2
Model_64_Hidden_Units_Results = model_64_HU.evaluate(x_test, y_test)
```

Show hidden output

```
Model_64_Hidden_Units_Results
```

```
[0.28239837288856506, 0.8865600228309631]
```

Using Trained data to predict

```
model_64_HU.predict(x_test)
```

Show hidden output

5. Model With MSE Loss

```
Model_MSE_LOSS = model_mse.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

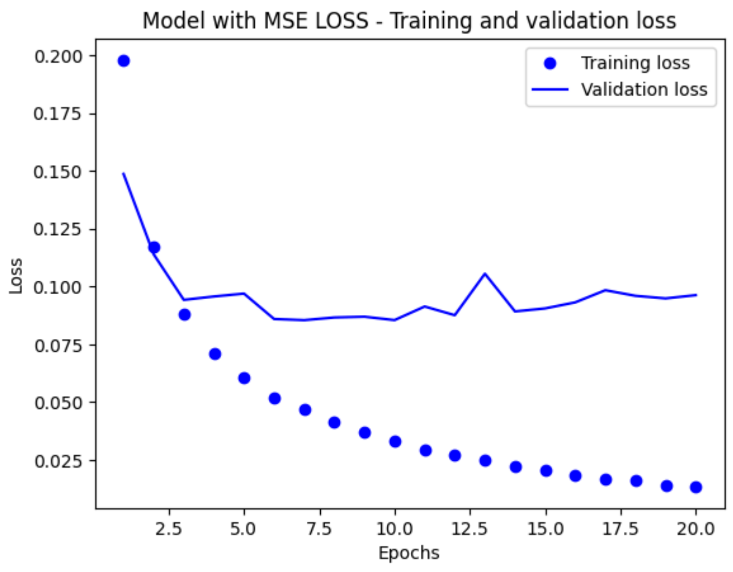
Show hidden output

```
Model_MSE_LOSS_dict = Model_MSE_LOSS.history
Model_MSE_LOSS_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

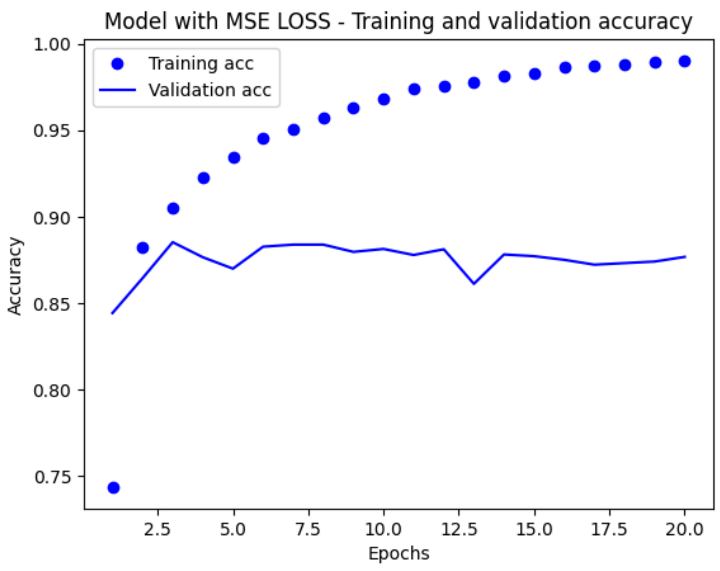
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_MSE_LOSS_dict = Model_MSE_LOSS.history
loss_values_MSE = Model_MSE_LOSS_dict["loss"]
val_loss_values_MSE = Model_MSE_LOSS_dict["val_loss"]
epochs = range(1, len(loss_values_MSE) + 1)
plt.plot(epochs, loss_values_MSE, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_MSE, "b", label="Validation loss")
plt.title("Model with MSE LOSS - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_MSE = Model_MSE_LOSS_dict["accuracy"]
val_acc_MSE = Model_MSE_LOSS_dict["val_accuracy"]
plt.plot(epochs, acc_MSE, "bo", label="Training acc")
plt.plot(epochs, val_acc_MSE, "b", label="Validation acc")
plt.title("Model with MSE LOSS - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_mse = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model_mse.compile(optimizer="rmsprop",
              loss="mse", # MSE Loss Function
              metrics=["accuracy"])
model_mse.fit(x_train, y_train, epochs=4, batch_size=512) # Epochs selected 2 because it starts to dip from 2
Model_MSE_LOSS_Results = model_mse.evaluate(x_test, y_test)
```

Show hidden output

```
Model_MSE_LOSS_Results
```

```
[0.08467386662960052, 0.8850399851799011]
```

Using Trained data to predict

```
model_mse.predict(x_test)
```

Show hidden output

6. Model With tanh activation

```
Model_TANH_ACT = model_tanh.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

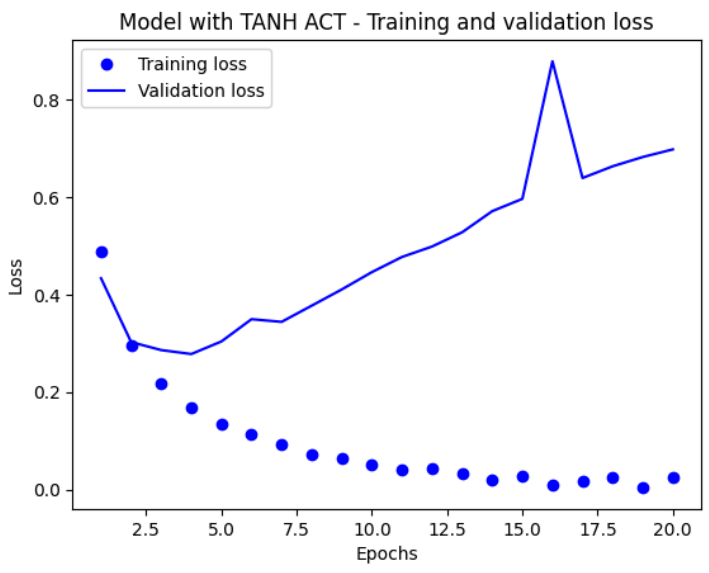
Show hidden output

```
Model_TANH_ACT_dict = Model_TANH_ACT.history
Model_TANH_ACT_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

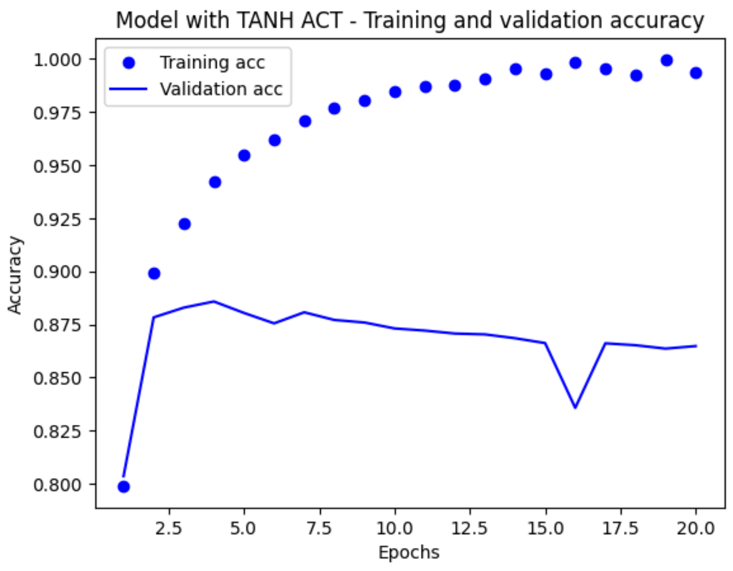
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_TANH_ACT_dict = Model_TANH_ACT.history
loss_values_TANH = Model_TANH_ACT_dict["loss"]
val_loss_values_TANH = Model_TANH_ACT_dict["val_loss"]
epochs = range(1, len(loss_values_TANH) + 1)
plt.plot(epochs, loss_values_TANH, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_TANH, "b", label="Validation loss")
plt.title("Model with TANH ACT - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_TANH = Model_TANH_ACT_dict["accuracy"]
val_acc_TANH = Model_TANH_ACT_dict["val_accuracy"]
plt.plot(epochs, acc_TANH, "bo", label="Training acc")
plt.plot(epochs, val_acc_TANH, "b", label="Validation acc")
plt.title("Model with TANH ACT - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_tanh = keras.Sequential([
    layers.Dense(16, activation="tanh"), # tanh activation
    layers.Dense(16, activation="tanh"), # tanh activation
    layers.Dense(1, activation="sigmoid")
])
model_tanh.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_tanh.fit(x_train, y_train, epochs=3, batch_size=512) # Epochs selected 3 because it starts to dip from 3
Model_TANH_ACT_Results = model_tanh.evaluate(x_test, y_test)
```

Show hidden output

```
Model_TANH_ACT_Results
```

```
[0.2895728051662445, 0.8831200003623962]
```

Using Trained data to predict

```
model_tanh.predict(x_test)
```

Show hidden output

7. Model With L2 Regularization

```
Model_Reg_Tech = model_reg.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

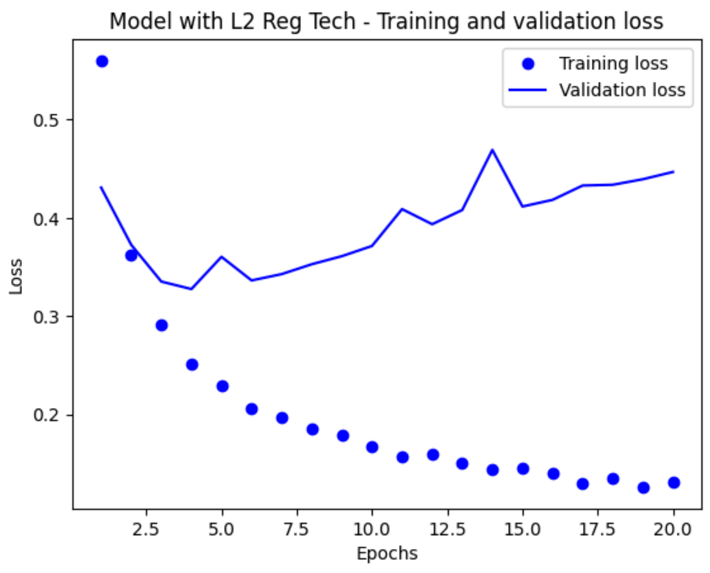
Show hidden output

```
Model_Reg_Tech_dict = Model_Reg_Tech.history
Model_Reg_Tech_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

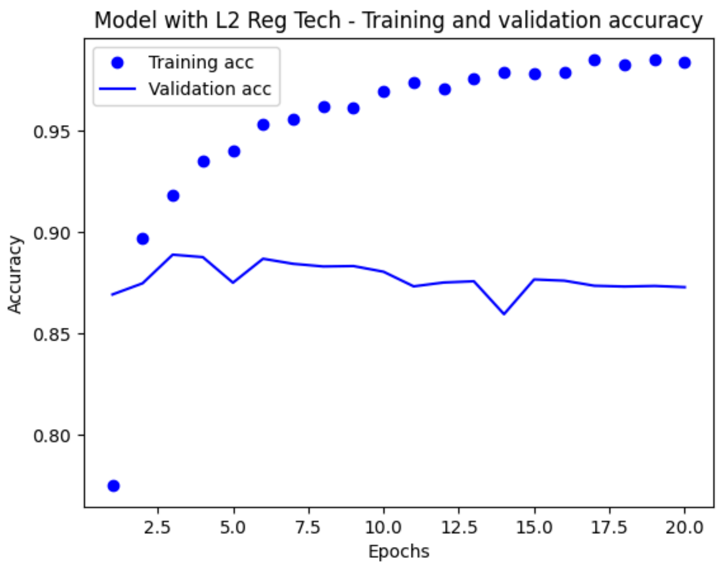
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_Reg_Tech_dict = Model_Reg_Tech.history
loss_values_Reg = Model_Reg_Tech_dict["loss"]
val_loss_values_Reg = Model_Reg_Tech_dict["val_loss"]
epochs = range(1, len(loss_values_Reg) + 1)
plt.plot(epochs, loss_values_Reg, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_Reg, "b", label="Validation loss")
plt.title("Model with L2 Reg Tech - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_Reg = Model_Reg_Tech_dict["accuracy"]
val_acc_Reg = Model_Reg_Tech_dict["val_accuracy"]
plt.plot(epochs, acc_Reg, "bo", label="Training acc")
plt.plot(epochs, val_acc_Reg, "b", label="Validation acc")
plt.title("Model with L2 Reg Tech - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_reg = keras.Sequential([
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common acc
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common acc
    layers.Dense(1, activation="sigmoid")
])
model_reg.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_reg.fit(x_train, y_train, epochs=2, batch_size=512) # Epochs selected 2 because it starts to dip from 3
Model_Reg_Tech_Results = model_reg.evaluate(x_test, y_test)
```

Show hidden output

```
Model_Reg_Tech_Results
```

```
[0.3397141396999359, 0.8874800205230713]
```

Using Trained data to predict

```
model_reg.predict(x_test)
```

Show hidden output

8. Model With Dropout Technique`

```
Model_Drp_Tech = model_drp.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

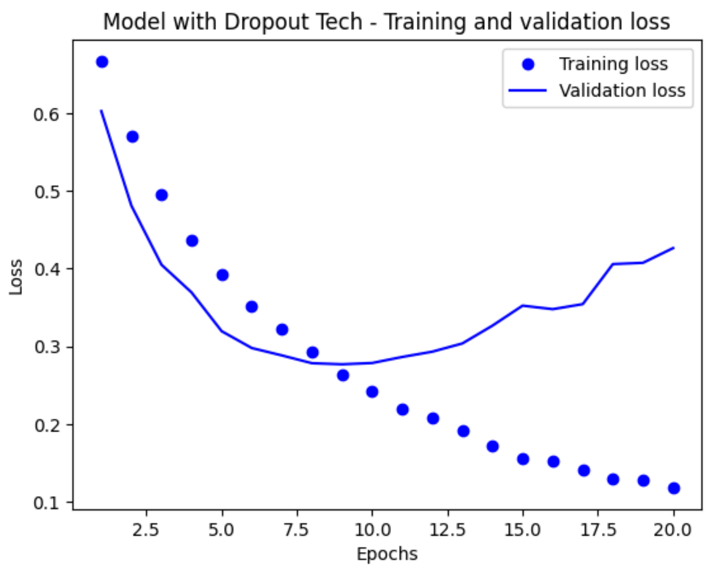
Show hidden output

```
Model_Drp_Tech_dict = Model_Drp_Tech.history
Model_Drp_Tech_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

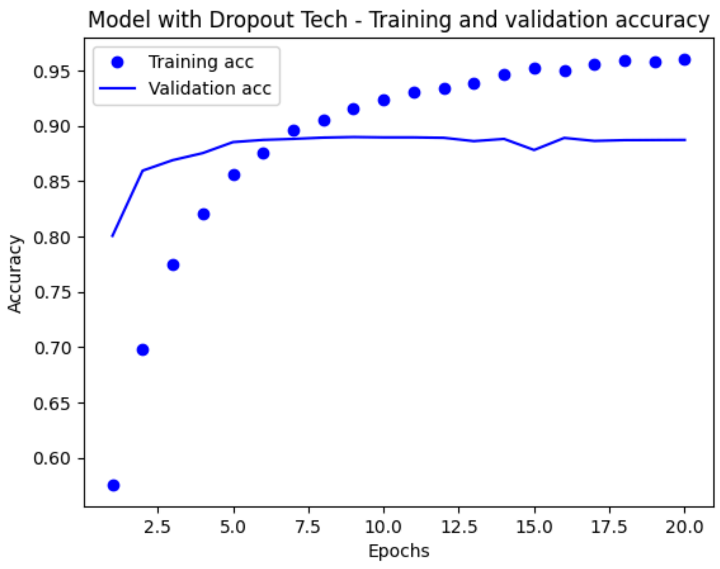
Plotting the graphshowing training and validation loss

```
import matplotlib.pyplot as plt
Model_Drp_Tech_dict = Model_Drp_Tech.history
loss_values_Drp = Model_Drp_Tech_dict["loss"]
val_loss_values_Drp = Model_Drp_Tech_dict["val_loss"]
epochs = range(1, len(loss_values_Drp) + 1)
plt.plot(epochs, loss_values_Drp, "bo", label="Training loss")
plt.plot(epochs, val_loss_values_Drp, "b", label="Validation loss")
plt.title("Model with Dropout Tech - Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



Plotting Accuracy

```
plt.clf()
acc_Drp = Model_Drp_Tech_dict["accuracy"]
val_acc_Drp = Model_Drp_Tech_dict["val_accuracy"]
plt.plot(epochs, acc_Drp, "bo", label="Training acc")
plt.plot(epochs, val_acc_Drp, "b", label="Validation acc")
plt.title("Model with Dropout Tech - Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Retraining

```
model_drp = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(1, activation="sigmoid")
])
model_drp.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model_drp.fit(x_train, y_train, epochs=9, batch_size=512) # Epochs selected 9 because it starts to stablize from 9
Model_Drp_Tech_Results = model_drp.evaluate(x_test, y_test)
```

Show hidden output

```
Model_Drp_Tech_Results
```

```
[0.34080618619918823, 0.8829600214958191]
```

Using Trained data to predict

```
model_drp.predict(x_test)
```

Show hidden output

Comparison of the Models

Retrieveing the training history for all models (For Organising)

```
Base_model_dict = Base_model.history
Base_model_dict.keys()

Model_1_Hidden_Layer_dict = Model_1_Hidden_Layer.history
Model_1_Hidden_Layer_dict.keys()

Model_3_Hidden_Layer_dict = Model_3_Hidden_Layer.history
Model_3_Hidden_Layer_dict.keys()

Model_32_Hidden_Units_dict = Model_32_Hidden_Units.history
Model_32_Hidden_Units_dict.keys()

Model_64_Hidden_Units_dict = Model_64_Hidden_Units.history
Model_64_Hidden_Units_dict.keys()

Model_MSE_LOSS_dict = Model_MSE_LOSS.history
Model_MSE_LOSS_dict.keys()

Model_TANH_ACT_dict = Model_TANH_ACT.history
Model_TANH_ACT_dict.keys()

Model_Reg_Tech_dict = Model_Reg_Tech.history
Model_Reg_Tech_dict.keys()

Model_Drp_Tech_dict = Model_Drp_Tech.history
Model_Drp_Tech_dict.keys()
```

```
dict_keys(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
```

Question 1 - Comparing Hidden layers with Base Model

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_1_Hidden_Layer": Model_1_Hidden_Layer,
    "Model_3_Hidden_Layer": Model_3_Hidden_Layer,
}

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})")

    plt.title(f'{metric.capitalize()} Comparison Across Models')
    plt.xlabel('Epochs')
    plt.ylabel(metric.capitalize())
    plt.legend()
    plt.show()
```

```
# Plot validation accuracy
plot_metrics('val_accuracy')

# Plot validation loss
plot_metrics('val_loss')

plot_metrics('accuracy')

plot_metrics('loss')
```

Show hidden output

Question 2 - Comparing Base model with Hidden Units value of 16, 32 and 64

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_32_Hidden_Units": Model_32_Hidden_Units,
    "Model_64_Hidden_Units": Model_64_Hidden_Units,
}

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})")

    plt.title(f'{metric.capitalize()} Comparison Across Models')
    plt.xlabel('Epochs')
    plt.ylabel(metric.capitalize())
    plt.legend()
    plt.show()

# Plot validation accuracy
plot_metrics('val_accuracy')

# Plot validation loss
plot_metrics('val_loss')

plot_metrics('accuracy')

plot_metrics('loss')
```

Show hidden output

Question 3 - Comparing of MSE loss function

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_MSE_Loss": Model_MSE_LOSS,
 }

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})")

    plt.title(f'{metric.capitalize()} Comparison Across Models')
    plt.xlabel('Epochs')
    plt.ylabel(metric.capitalize())
    plt.legend()
    plt.show()

# Plot validation accuracy
plot_metrics('val_accuracy')
```

```
# Plot validation loss
plot_metrics('val_loss')

plot_metrics('accuracy')

plot_metrics('loss')
```

Show hidden output

Question 4 - Comparing of Tanh activation with base model

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_TANH_Activation": Model_TANH_ACT,
}

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})")

    plt.title(f'{metric.capitalize()} Comparison Across Models')
    plt.xlabel('Epochs')
    plt.ylabel(metric.capitalize())
    plt.legend()
    plt.show()

# Plot validation accuracy
plot_metrics('val_accuracy')

# Plot validation loss
plot_metrics('val_loss')

plot_metrics('accuracy')

plot_metrics('loss')
```

Show hidden output

Question 5 - Comparison of L2 regularization, Dropout and Base model

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_Regularization": Model_Reg_Tech,
    "Model_Dropout": Model_Drp_Tech
}

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})"

    plt.title(f'{metric.capitalize()} Comparison Across Models')
    plt.xlabel('Epochs')
    plt.ylabel(metric.capitalize())
    plt.legend()
    plt.show()

# Plot validation accuracy
plot_metrics('val_accuracy')

# Plot validation loss
plot_metrics('val_loss')
plot_metrics('accuracy')

plot metrics('loss')
```

Show hidden output

Comparing all the models

```
import matplotlib.pyplot as plt

# Dictionary of models and their histories
model_histories = {
    "Base_Model": Base_model,
    "Model_1_Hidden_Layer": Model_1_Hidden_Layer,
    "Model_3_Hidden_Layer": Model_3_Hidden_Layer,
    "Model_32_Hidden_Units": Model_32_Hidden_Units,
    "Model_64_Hidden_Units": Model_64_Hidden_Units,
    "Model_MSE_Loss": Model_MSE_LOSS,
    "Model_TANH_Activation": Model_TANH_ACT,
    "Model_Regularization": Model_Reg_Tech,
    "Model_Dropout": Model_Drp_Tech
}

# Extract and display keys of histories
for model_name, model in model_histories.items():
    history_dict = model.history
    print(f"{model_name} history keys: {history_dict.keys()}")

# Function to plot training and validation accuracy/loss across models
def plot_metrics(metric):
    plt.figure(figsize=(10, 6))
    for model_name, model in model_histories.items():
        metric_values = model.history[metric]
        plt.plot(range(1, len(metric_values) + 1), metric_values, label=f"{model_name} ({metric})")
```