ADVANCED MACHINE LEARNING

ASSIGNMENT – 2

SUBMITTED BY

AJITH RAJ PERIYASAMY

Github Link:

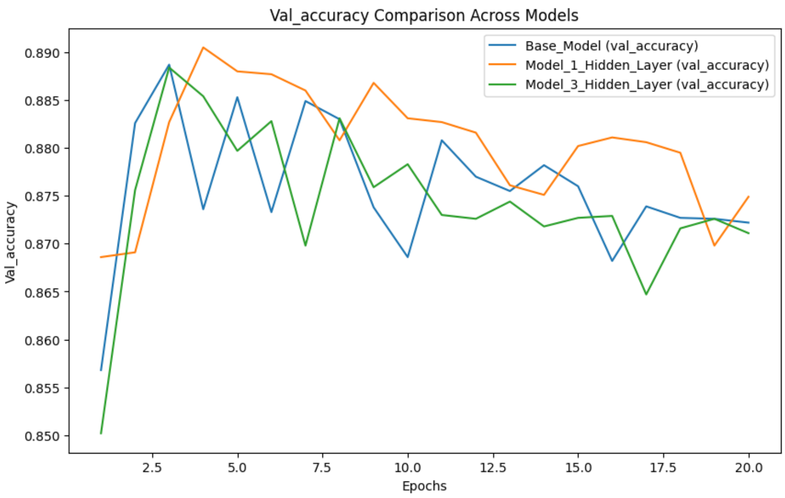
https://github.com/Ajith0719/aperiyas_64061/tree/main/Assignment%202

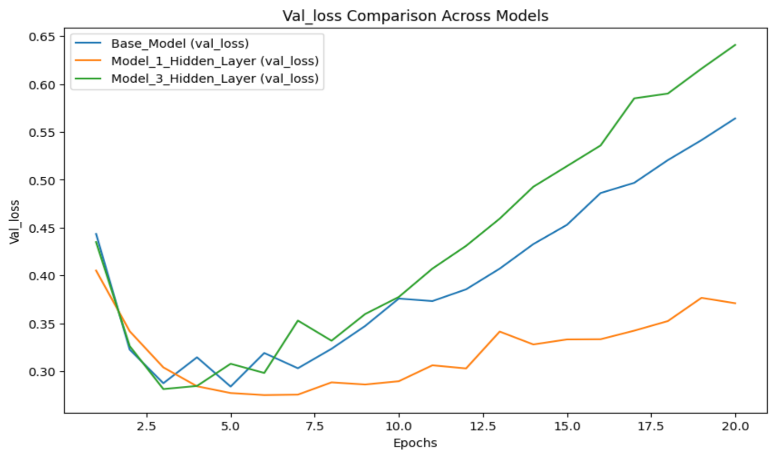
Case 1: You used two hidden layers. Try using one or three hidden layers and see how doing so affects validation and test accuracy.

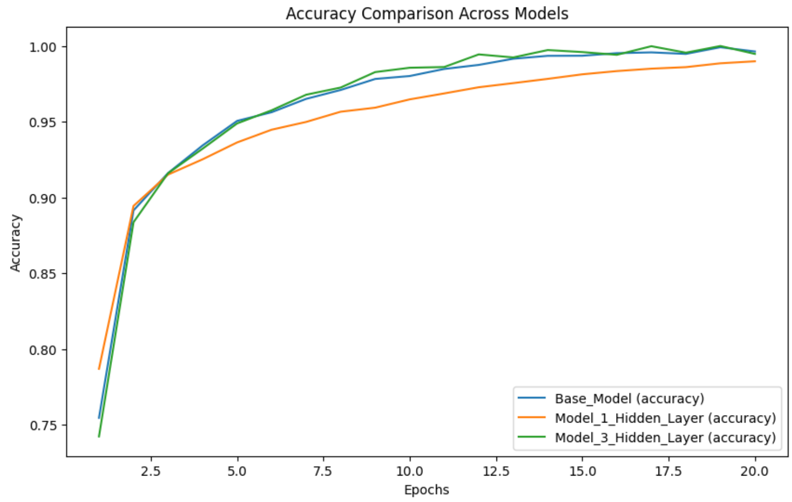
- The model with two hidden layers delivers the best performance, achieving the highest validation accuracy and the lowest loss, surpassing both the single-layer and three-layer models.
- The one-hidden-layer model performs slightly worse than the two-layer model in both training and validation accuracy.
- Adding a third hidden layer does not enhance performance; instead, it introduces instability, indicating that more layers do not always yield better results.
- Overall, the two-hidden-layer model strikes the best balance between accuracy and stability.

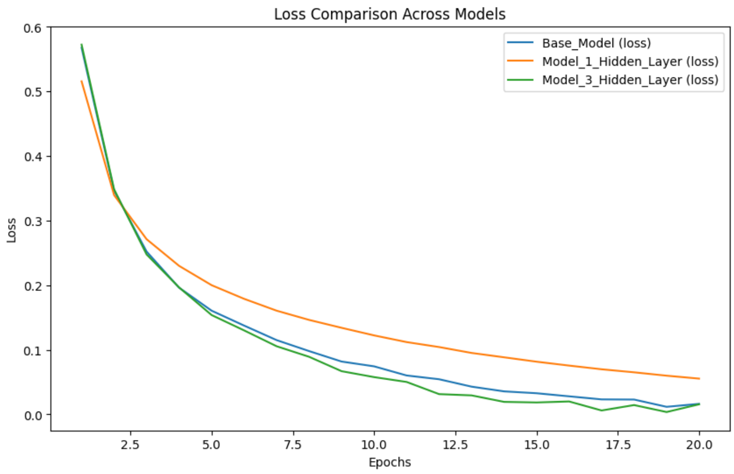
	Test loss	**Test Accuracy**
Base Model	0.29	0.88
1HL	0.29	0.89
3HL	0.37	0.87

*** Note the code snipping's will be attached at the end of the report.*





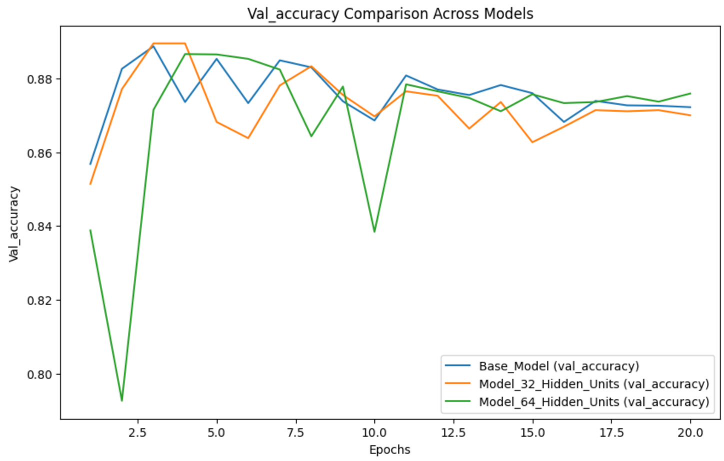


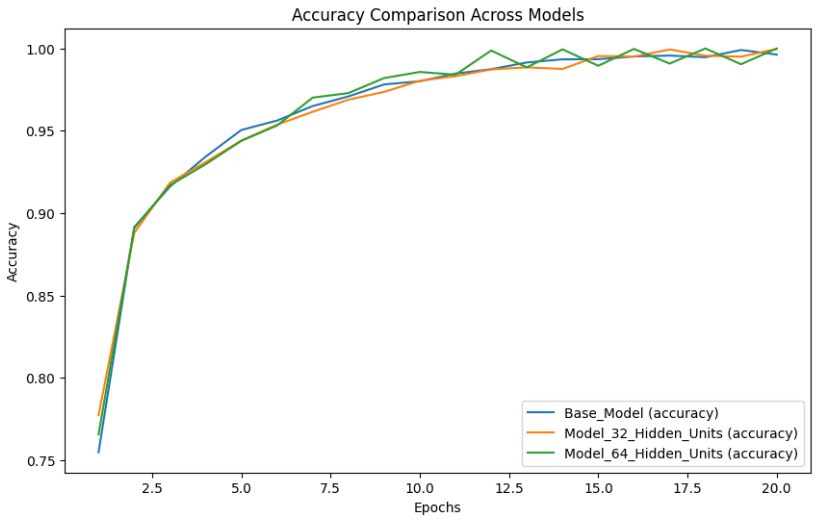


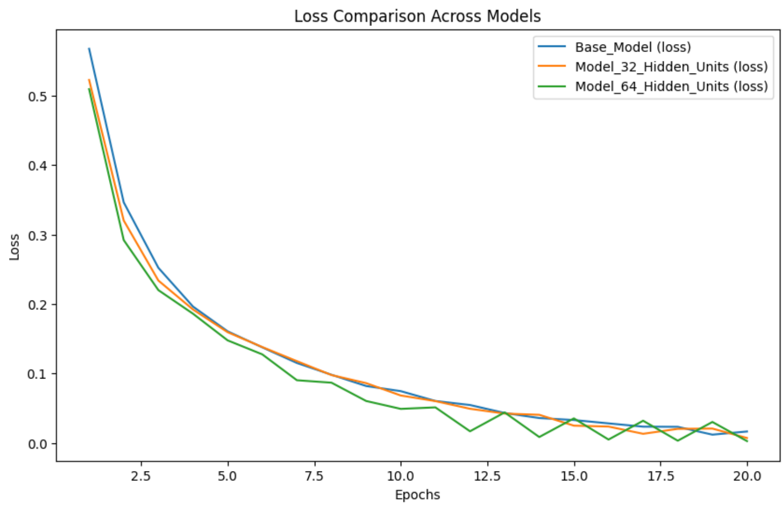
Case 2: Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on.

- In terms of validation accuracy, the model with 32 hidden units outperforms both the 16-unit and 64-unit models. While the 64-unit model exhibits more variability and lower validation accuracy, the 32-unit model performs similarly to the base 16-unit model.
- Despite having the lowest validation loss at higher epochs, the 64-unit model shows signs of overfitting, suggesting that simply increasing the number of hidden units does not necessarily improve generalization.
- Training accuracy and loss remain comparable across models with 16, 32, and 64 units, though the base model demonstrates slightly better overall performance.
- Ultimately, increasing the hidden units from 16 to 32 to 64 does not yield significant improvements and instead introduces more volatility, making the base model the more reliable choice.

	Test loss	Test Accuracy
Base Model	0.29	0.88
32HU	0.29	0.88
64HU	0.30	0.89



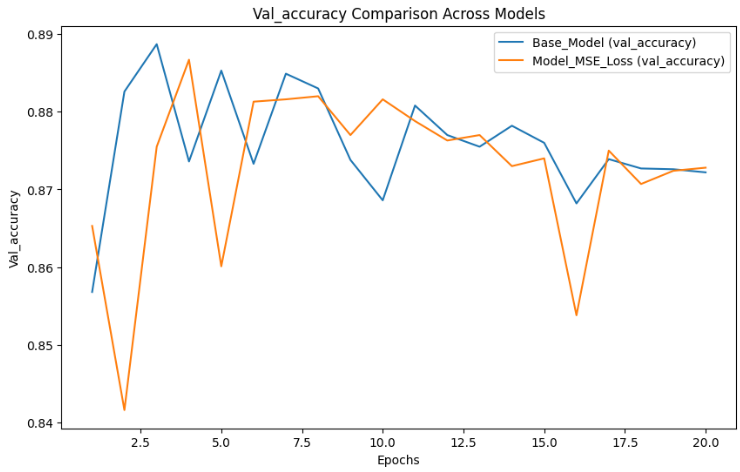


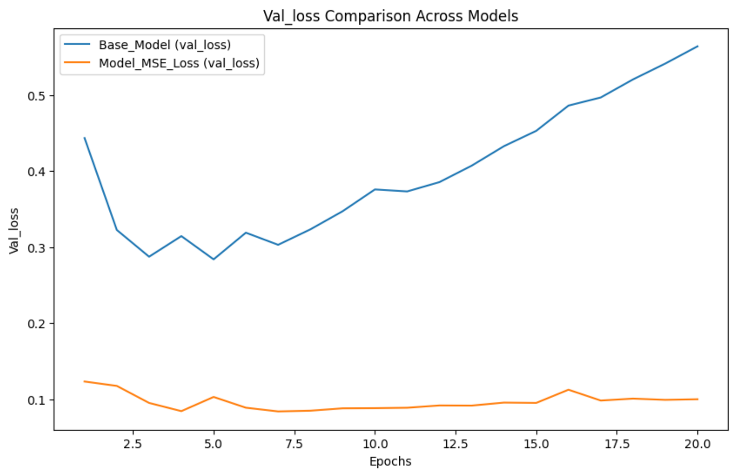


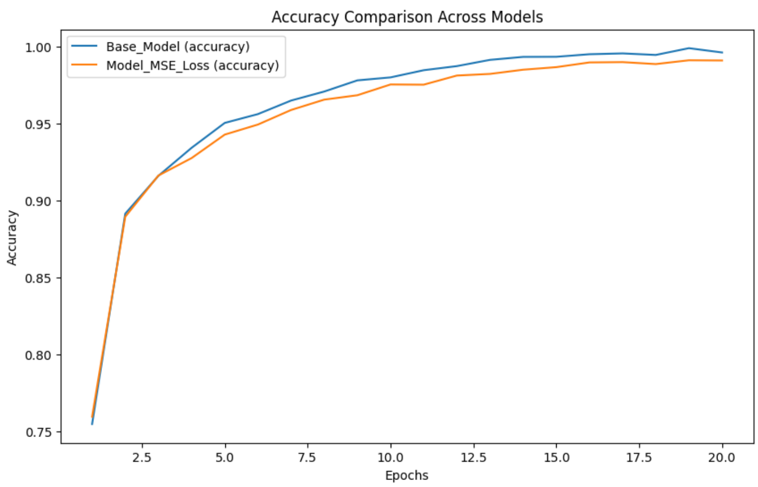
3. Try using the MSE loss function instead of binary cross entropy.

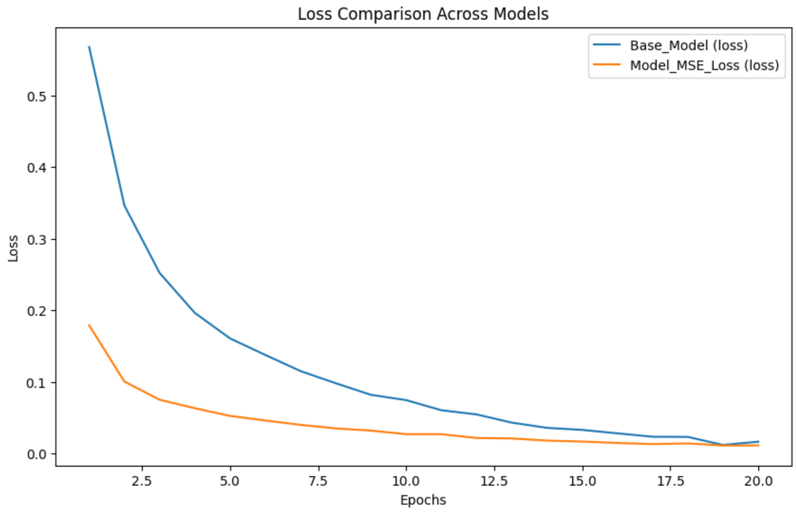
- BCE is better suited for binary classification problem, in this case the MSE performs significantly better than BCE.
- The MSE majorly outperforms in validation loss comparison, where it shows a lower val loss compared to the base model. This shows the MSE model is better able to minimize the error between predicted and true values.
- The MSE model gives better results with less training (with lesser EPOCHS)
- In conclusion the MSE model is clearly better than using BCE model for this specific model building.

	Test loss	Test Accuracy
Base Model	0.29	0.88
MSE	0.09	0.88





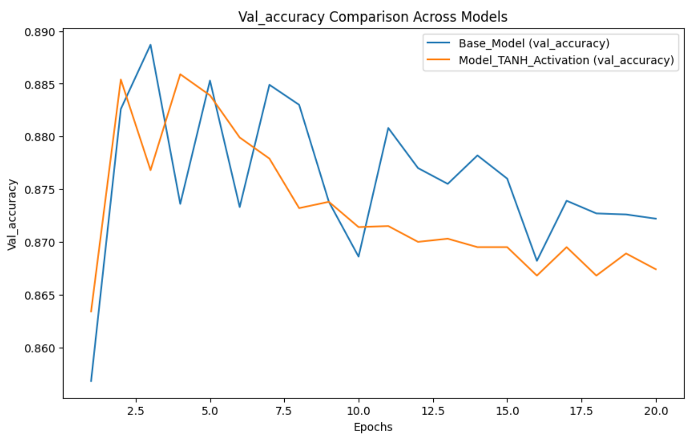


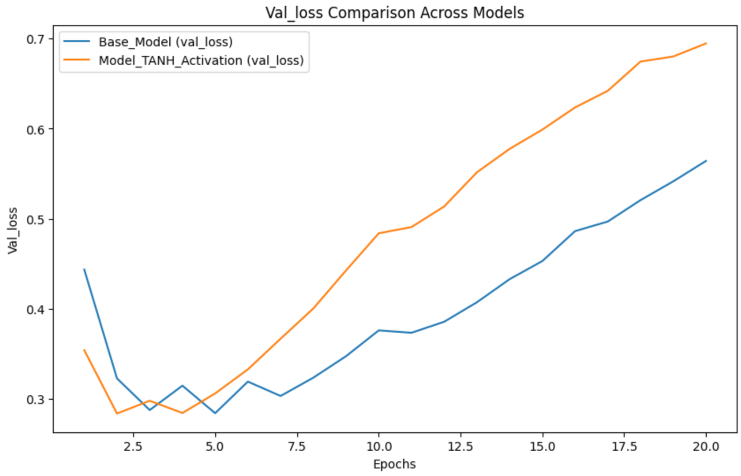


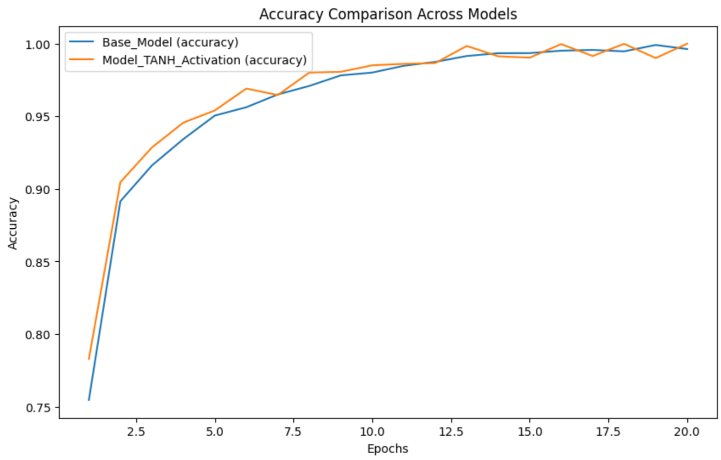
4. **Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of relu**

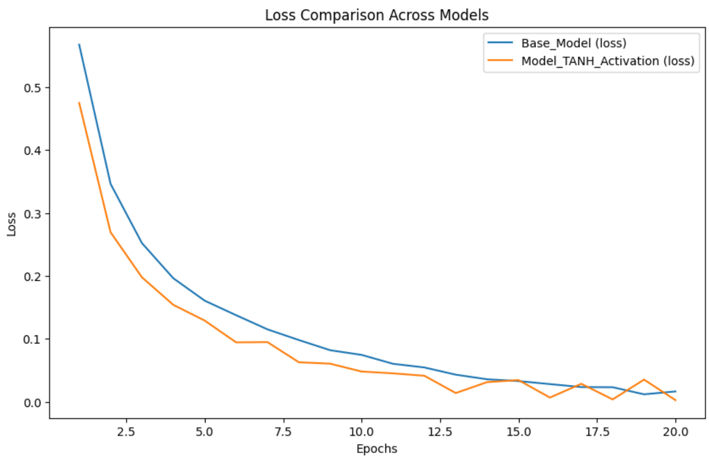
- The relu activation (Base line model) performs better than tanh activation, where relu's accuracy is better.
- Relu activation model shows a lower loss compared to the tanh model which shows that the relu model is better to minimize the error between predicted and true value.
- In conclusion, relu is a better option because it outperforms tanh in accuracy and has a lower loss.

	Test loss	**Test Accuracy**
Base Model	0.29	0.88
Tanh	0.29	0.87





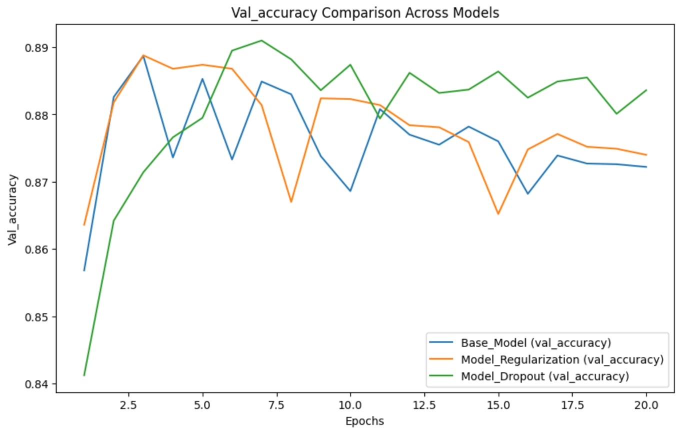


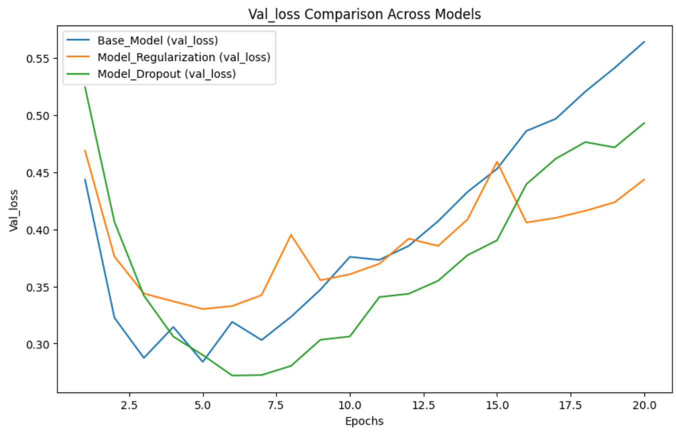


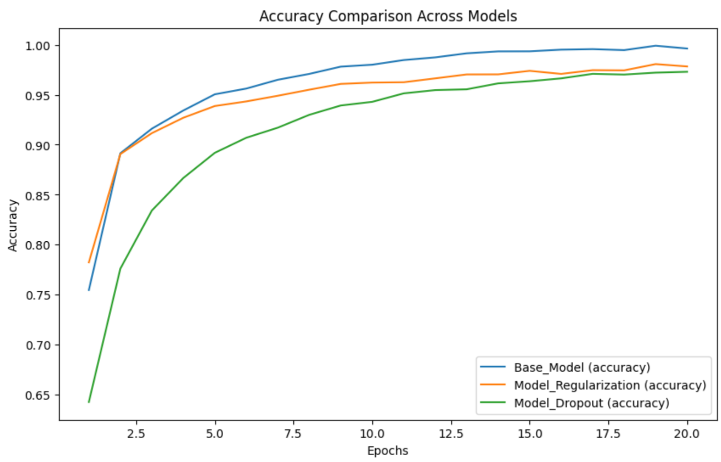
5. **Use any technique we studied in class, and these include regularization, dropout, etc., to get your model to perform better on validation.**

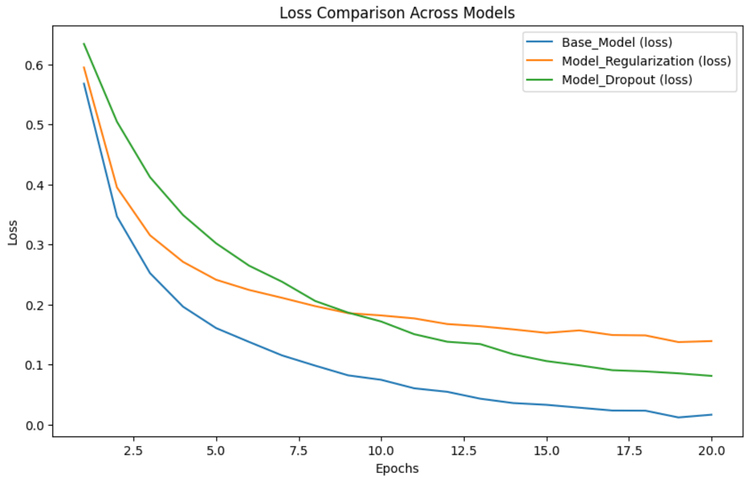
- Dropout optimization achieves the highest accuracy compared to both the baseline model and L2 regularization.
- It also performs best in terms of loss, showing the lowest error rate, with L2 following closely behind, while the baseline model is the least effective.
- Overall, based on the performance across all graphs, dropout proves to be the most effective optimization method for this model.

	Test loss	Test Accuracy
L2	0.34	0.88
Dropout	0.32	0.88





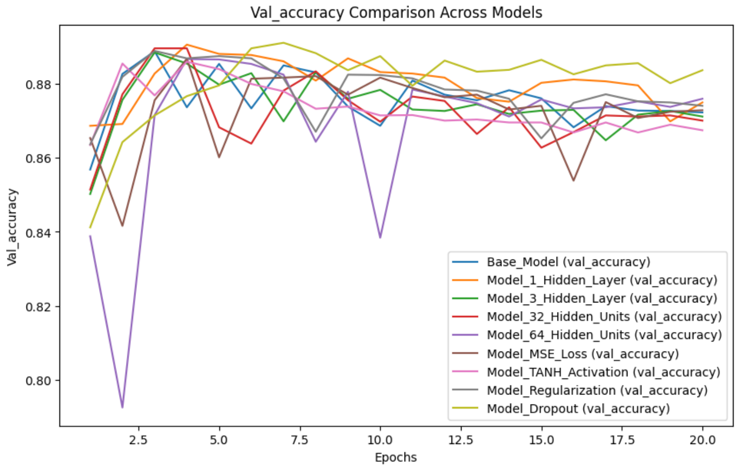


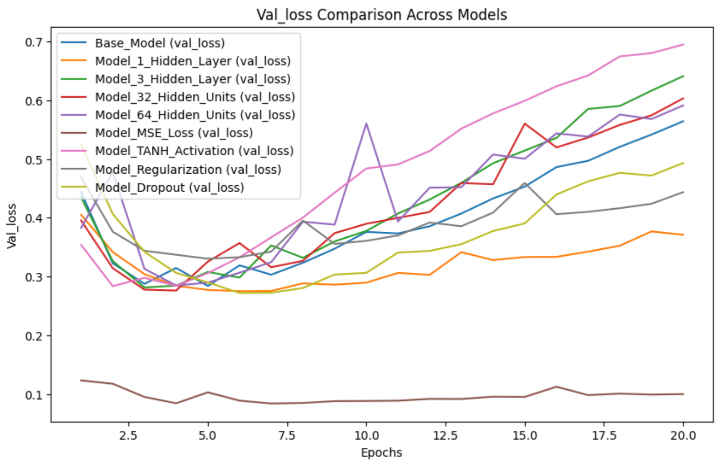


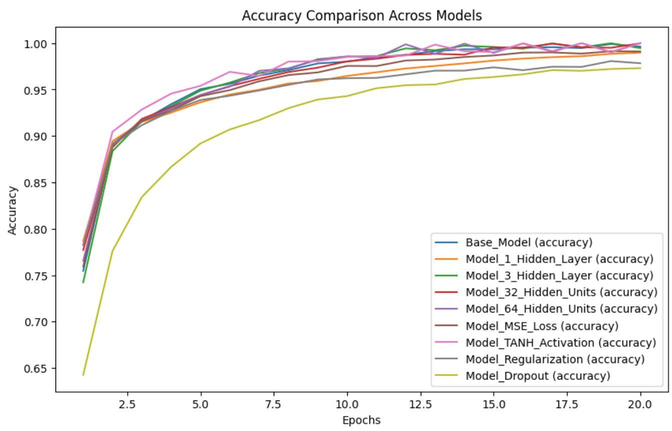
Comparison of all the models.

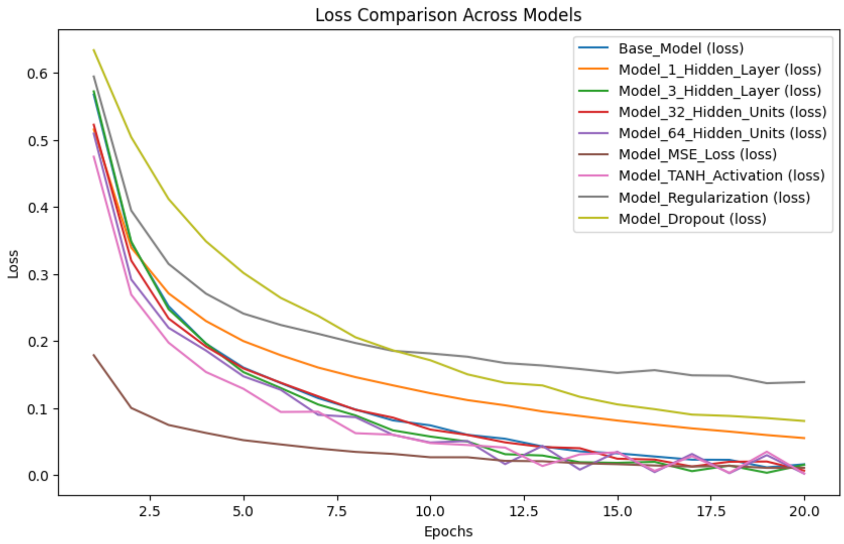
- Among all models, the one with 32 hidden units achieved the highest validation accuracy.
- In terms of overall accuracy, the Tanh activation model and the baseline model performed similarly and were the best in this comparison.
- When evaluating validation loss, the model with 64 hidden units showed the best performance.
- Overall, the 64 hidden units model provided a good balance and delivered consistently strong results across all metrics.

	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


Val_accuracy Comparison Across Models
Val_accuracy
Epochs
Base_Model (val_accuracy)
Model_1_Hidden_Layer (val_accuracy)
Model_3_Hidden_Layer (val_accuracy)
Model_32_Hidden_Units (val_accuracy)
Model_64_Hidden_Units (val_accuracy)
Model_MSE_Loss (val_accuracy)
Model_TANH_Activation (val_accuracy)
Model_Regularization (val_accuracy)
Model_Dropout (val_accuracy)


Val_loss Comparison Across Models
Val_loss
Epochs
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)


Accuracy Comparison Across Models
Accuracy
Epochs
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)



Following is the code explanation

- The dataset was loaded and prepared using the code provided by the professor.
- A total of nine different models were created to facilitate comparison.
- Each model was trained, and its accuracy and loss were plotted for analysis.
- Models were then retrained following the structure of the baseline model provided by the professor.
- Finally, all models were compared based on the given questions, with the results summarized above.

*** Because of the length of the model the google colab page was printed and attached at the end of the report.*

Loading the IMDB dataset

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

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
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):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        for j in sequence:
            results[i, j] = 1.
    return results
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")
```

Model with various configurations

1. Base 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"])
```

2. 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"])
```

3. Model with 3 hidden layers (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"])
```

4. 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"])
```

5. 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"])
```

6. 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"])
```

7. 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"])
```

8. Regularized Model (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
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common
    layers.Dense(1, activation="sigmoid")
])

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

9. 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:]
```

Model Training

1. Base Model

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

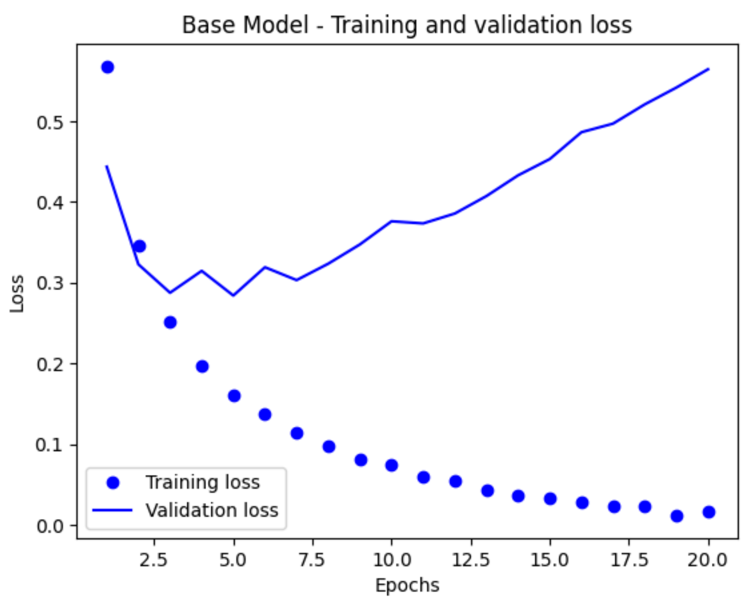
Show hidden output

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

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

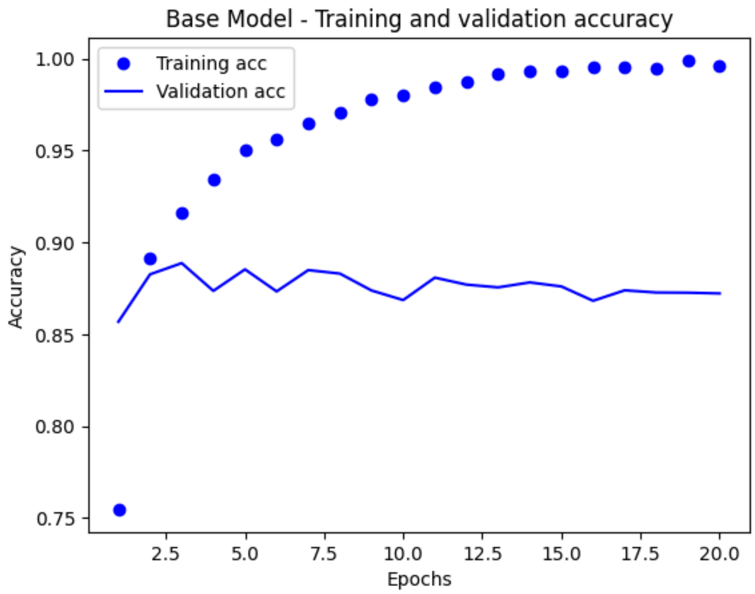
Graph showing training and validation loss

```
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
```

```
[0.28930649161338806, 0.8832799792289734]
```

Predictions

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

```
782/782 ━━━━━━━━━━━━━━━━━━━━ 1s 920us/step
array([[0.20052755],
       [0.9999643 ],
       [0.89107907],
       ...,
       [0.08803749],
       [0.0890219 ],
       [0.50929415]], dtype=float32)
```

2. 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))
```

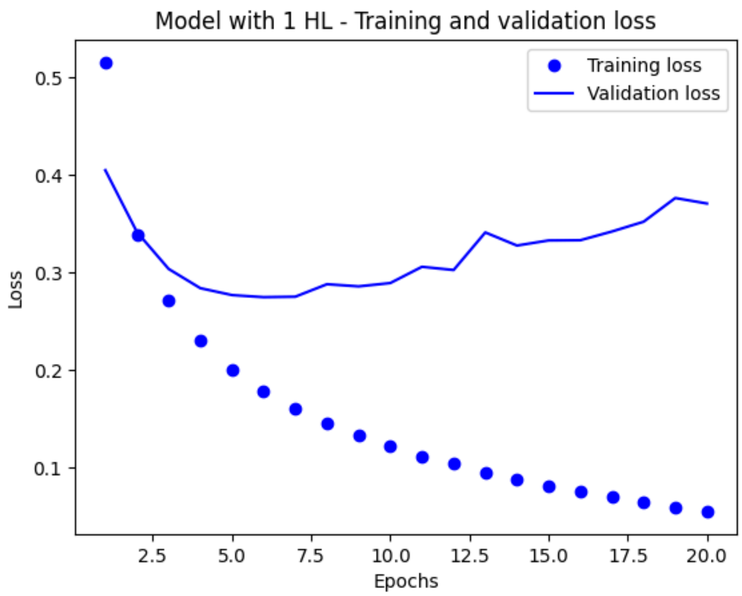
Show hidden output

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

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

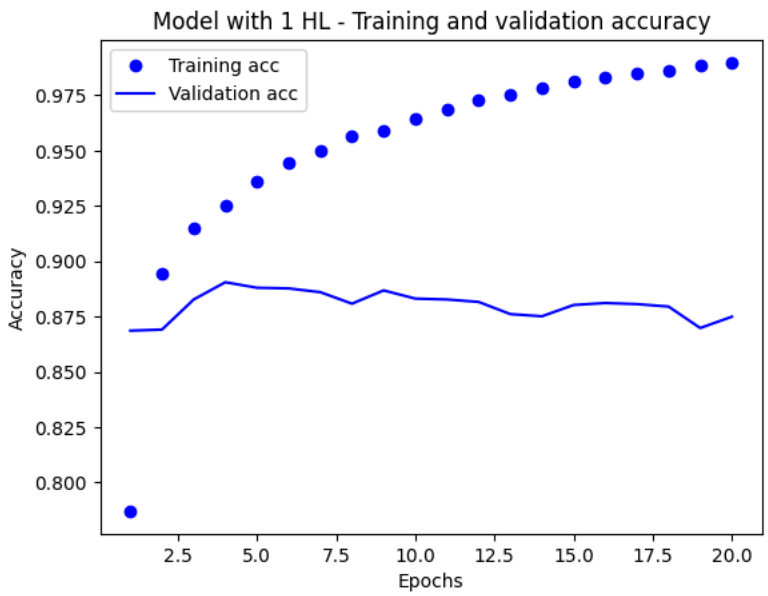
Graph showing training and validation loss

```
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
```

```
[0.27956831455230713, 0.8889600038528442]
```

Predictions

```
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

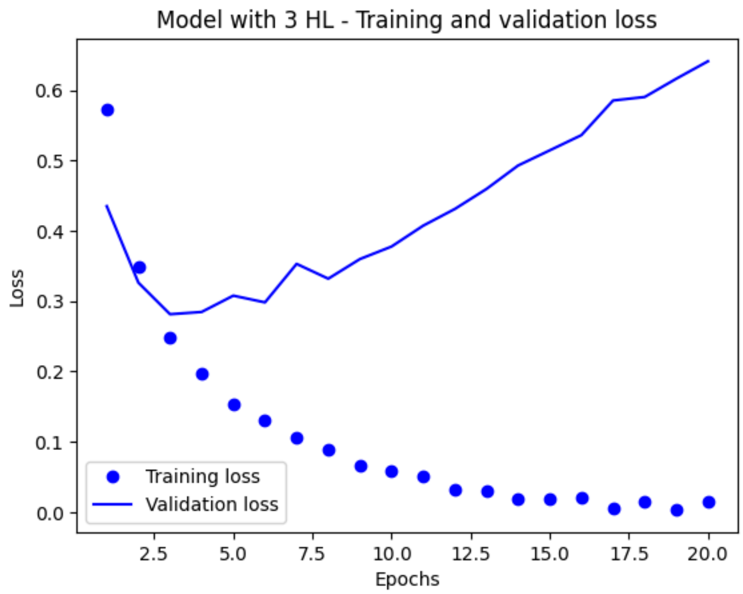
```
Model_3_Hidden_Layer_dict = Model_3_Hidden_Layer.history
Model_3_Hidden_Layer_dict.keys()
```

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

Graph showing training and validation loss

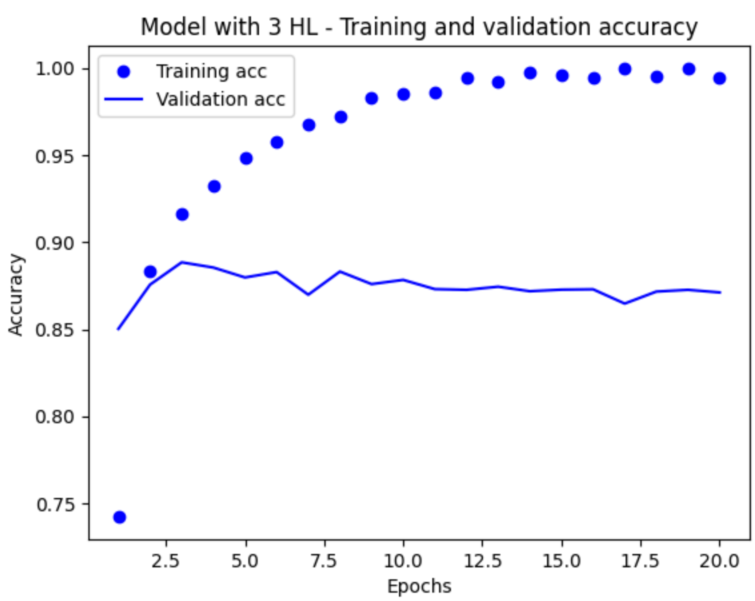
```
import matplotlib.pyplot as plt
Model_3_Hidden_Layer_dict = Model_3_Hidden_Layer.history
loss_values_3 = Model_3_Hidden_Layer_dict["loss"]
val_loss_values_3 = Model_3_Hidden_Layer_dict["val_loss"]
```

```
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
```

```
[0.3324761390686035, 0.8776400089263916]
```

Predictions

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

```
782/782 ━━━━━━━━━━━━━━━━━━━━ 1s 989us/step
array([[0.10691544],
       [0.9999927 ],
       [0.7307757 ],
       ...,
       [0.09161345],
       [0.03029524],
       [0.7180867 ]], dtype=float32)
```

4. 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))
```

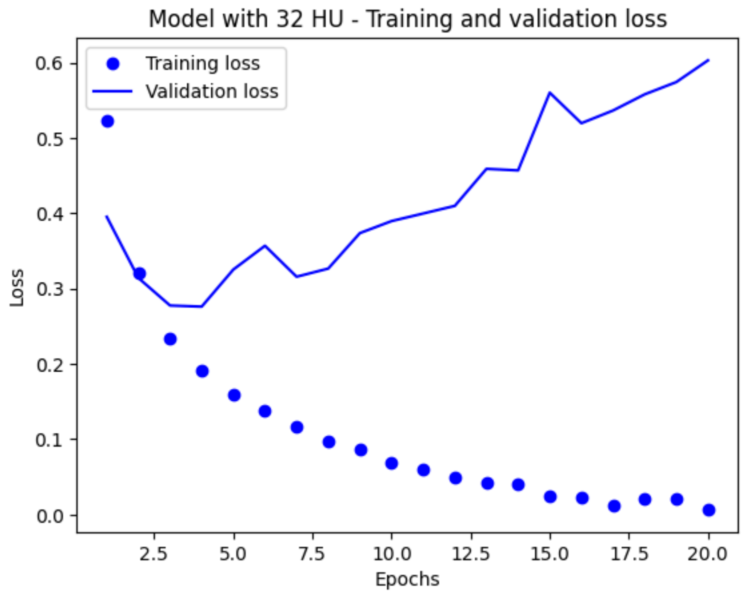
Show hidden output

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

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

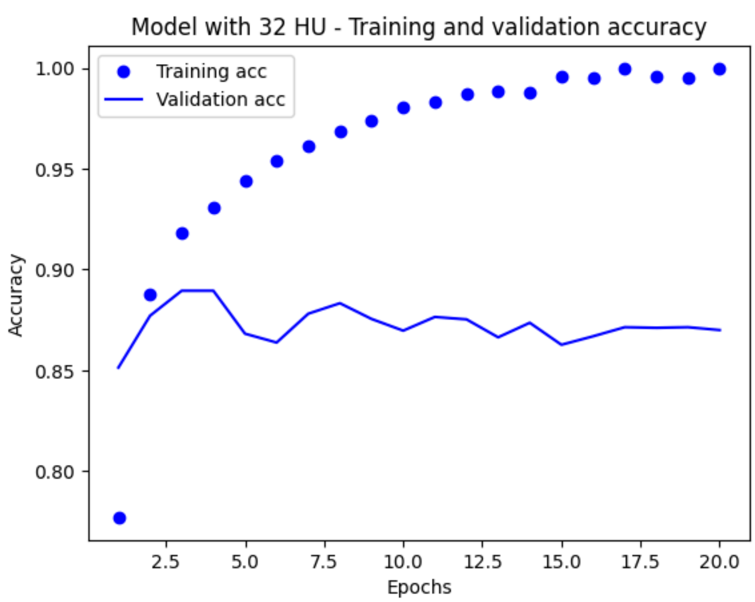
Graph showing training and validation loss

```
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
```

```
[0.2790932059288025, 0.8893600106239319]
```

Prediction

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

Show hidden output

5. 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))
```

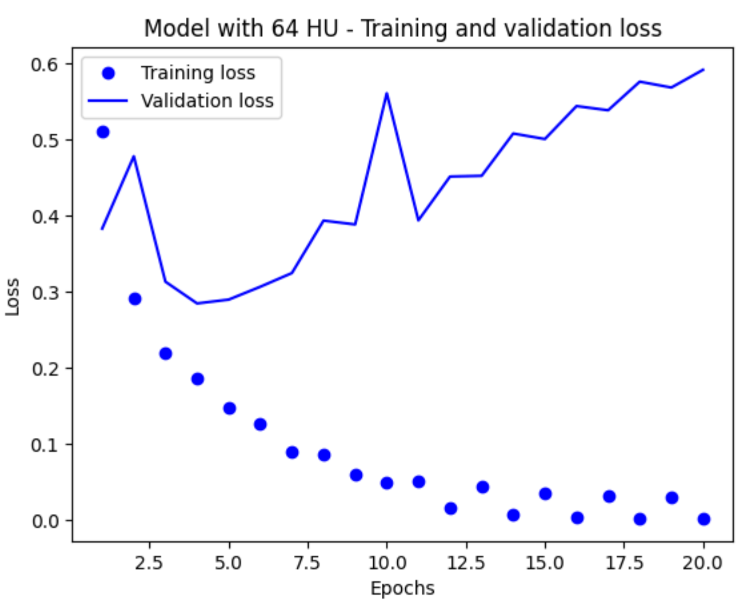
Show hidden output

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

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

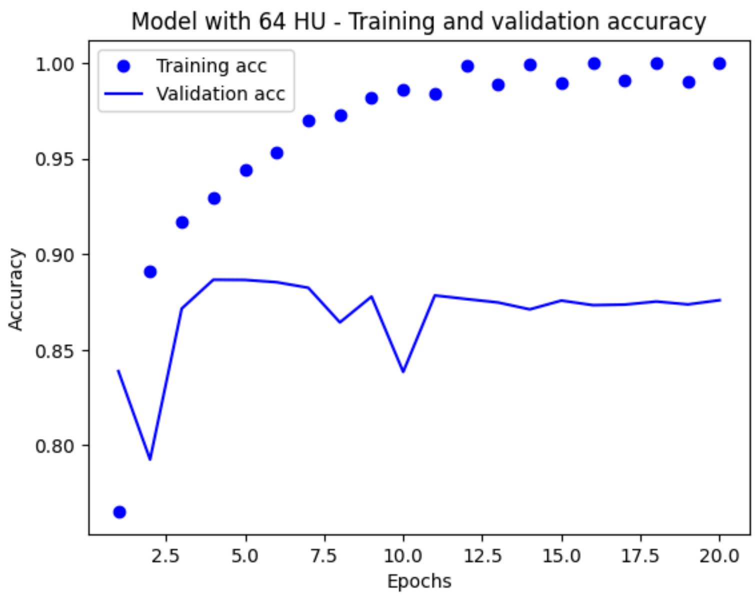
Graph showing training and validation loss

```
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
```

```
[0.3220630884170532, 0.8677200078964233]
```

Prediction

```
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))
```

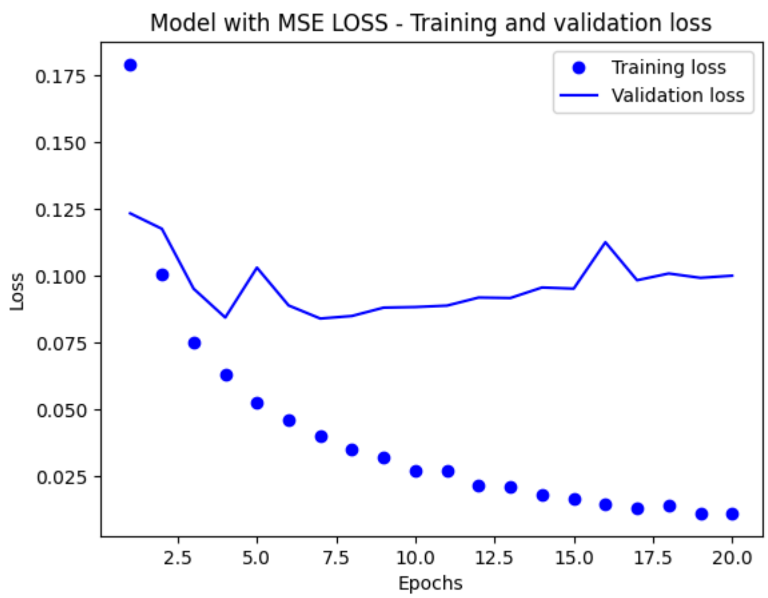
Show hidden output

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

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

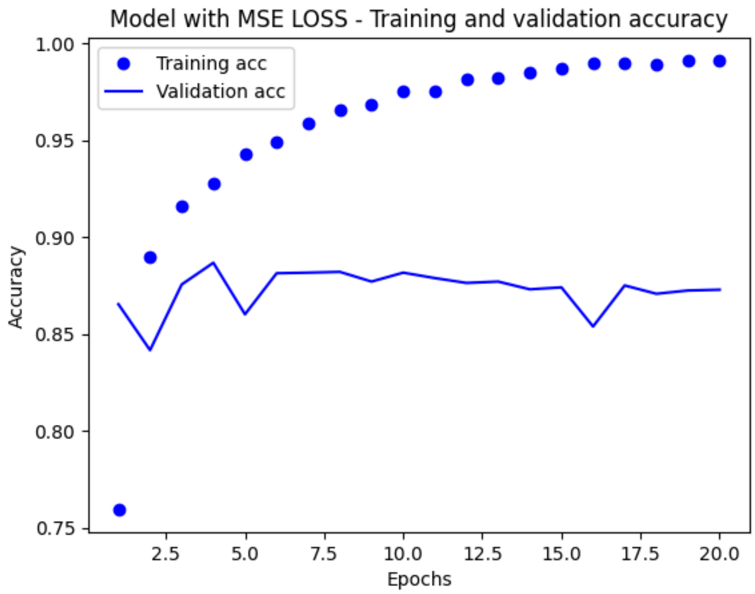
Graph showing training and validation loss

```
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
```

```
[0.08590194582939148, 0.884880006313324]
```

Prediction

```
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

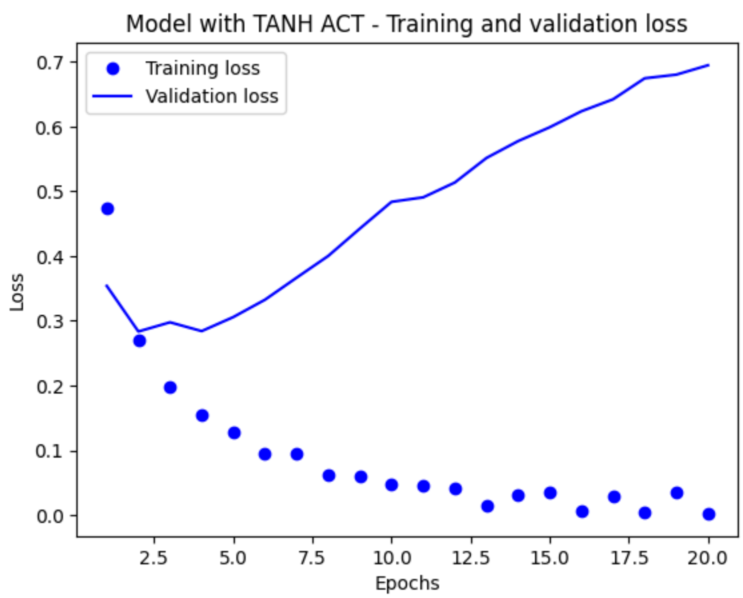
```
Model_TANH_ACT_dict = Model_TANH_ACT.history
Model_TANH_ACT_dict.keys()
```

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

Graph showing training and validation loss

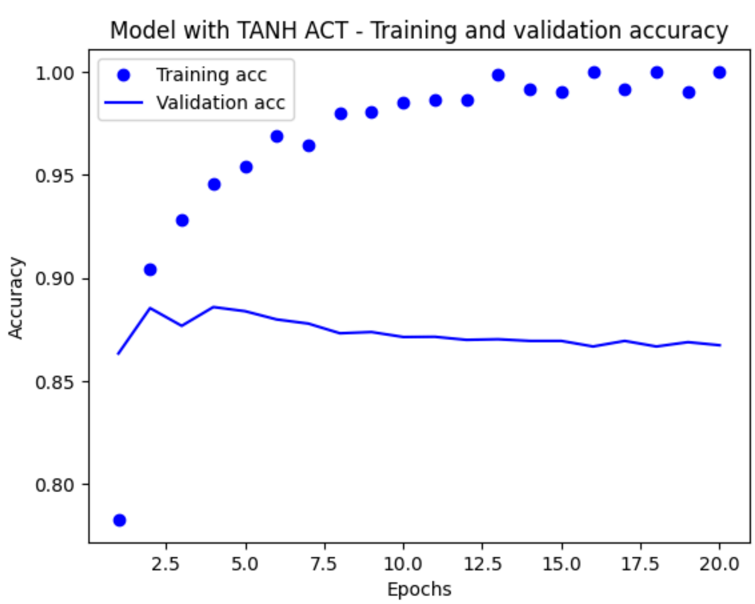
```
import matplotlib.pyplot as plt
Model_TANH_ACT_dict = Model_TANH_ACT.history
loss_values_TANH = Model_TANH_ACT_dict["loss"]
```

```
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
```

```
[0.28239673376083374, 0.8858000040054321]
```

Prediction

```
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))
```

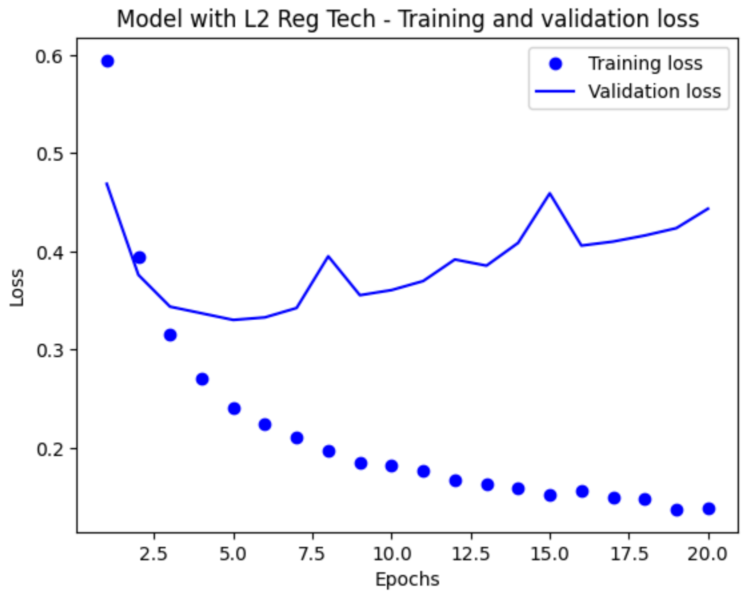
Show hidden output

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

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

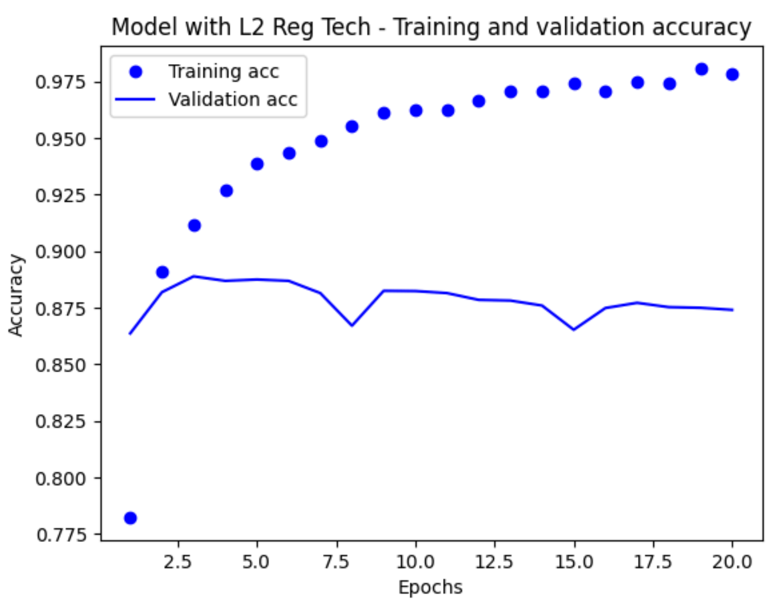
Graph showing training and validation loss

```
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
    layers.Dense(16, activation="relu", kernel_regularizer=regularizers.l2(0.001)), # Applied L2 regularization (0.001 - common
    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
```

```
[0.3455865979194641, 0.8848400115966797]
```

Using Trained data to predict

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

Show hidden output

9. Model With Dropout Technique

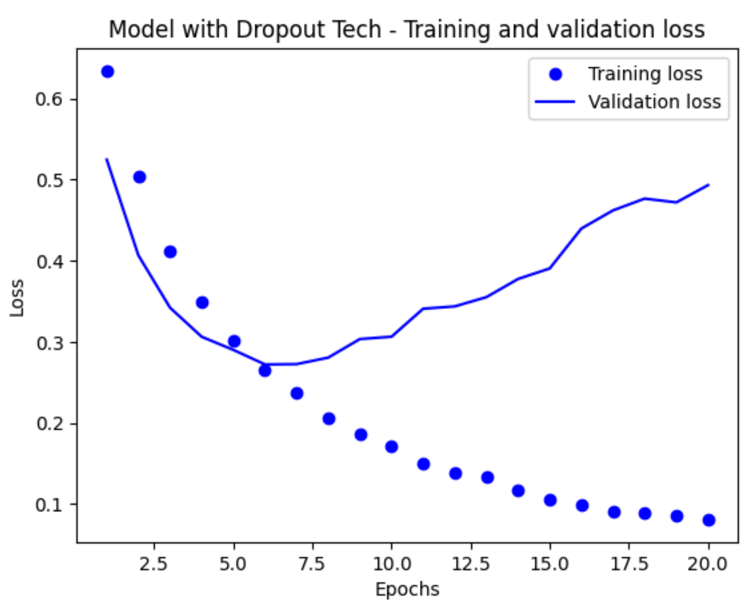
```
Model_Drp_Tech = model_drp.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

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

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

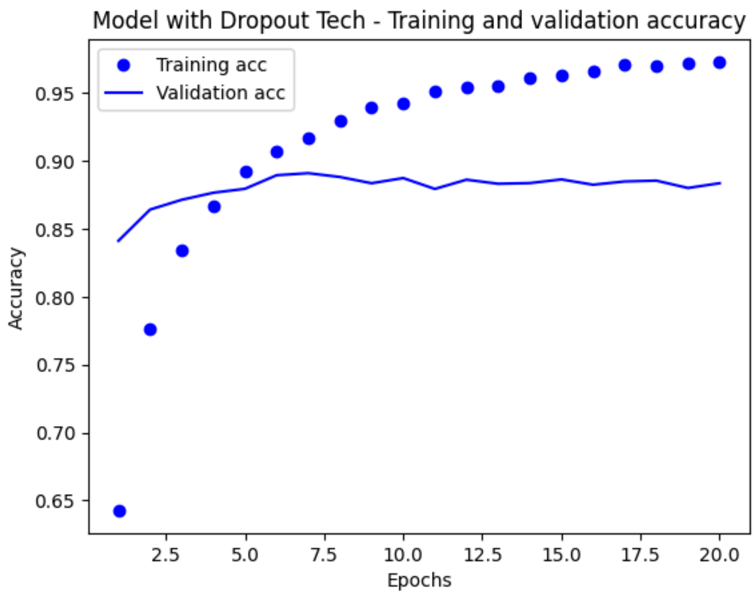
Graph showing training and validation loss

```
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
```

```
[0.34530577063560486, 0.8808799982070923]
```

Prediction

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

Show hidden output

Comparison of the Models

Fetching the training history for all models

```
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 - 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 Tanh activation with base model which has relu activation function

```
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')
```