#### Aim: To achieve a better model

**Past Model:** The best model was achieved by the following hyperparameters: batch\_size = 32, epochs = 100 and by applying two dense layers.

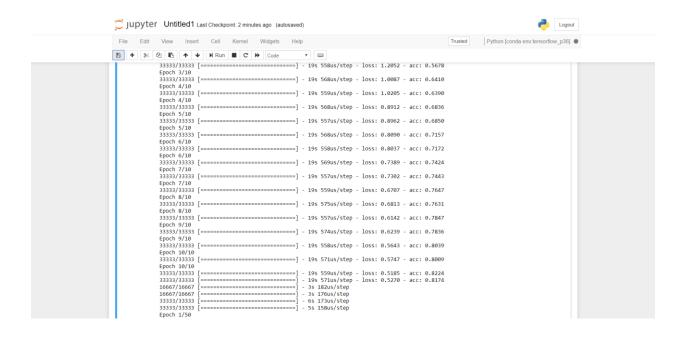
# **Defining a New Model:**

Through the presentation in the lecture we understood various other parameters we could tweak to achieve a better model with higher accuarcy.

### **Implementing Grid Search:**

For this purpose, we decided to use the grid search to derive the best paramaters between epochs and batch size rather that manually tuning the parameters. We also tried implementing the same for dropouts.

```
In [*]: # create model
    model = KerasClassifier(build fn=create model, verbose=1)
    # initiate RMSprop optimizer
    #opt = keras.optimizers.Adagrad(lr=0.01, epsilon=None, decay=0.0)
    # define the grid search parameters
    batch_size = [32, 70, 40]
    epochs = [10, 30, 50]
    param grid = dict(batch_size=batch_size, epochs=epochs)
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
    grid_result = grid.fit(x_train, y_train)
    print(grid_result)
    print("yes")
    Epoch 1/10
    Epoch 1/10
     320/33333 [.....] - ETA: 4:01 - loss: 3.6078 - acc: 0.1094Epoch 1/10
    Epoch 2/10
    Epoch 3/10
    Epoch 4/10
```



```
In [*]: # create model
    model = KerasClassifier(build_fn=create_model, verbose=1)
    # define the grid search parameters
    # define the grid search parameters
batch_size = [32,64,128]
epochs = [20,30,40]
param_grid = dict(batch_size=batch_size, epochs=epochs)
grid = GridsearchCV(estimator=model, param_grid=param_grid, n_jobs=-1)
grid_result = grid.fit(x_train, y_train)
    print(grid_result)
print("yes")
    Epoch 1/20
    Epoch 3/20
    Epoch 4/20
    Epoch 5/20
    Epoch 6/20
```

```
Epoch 13/20
3333/33333 [=========] - 17s 516us/step - loss: 0.3837 - acc: 0.8690 Epoch 15/20
33333/33333 [
            Epoch 16/20
33333/33333 [:
           -----] - 11s 328us/step - loss: 0.3104 - acc: 0.8972
Epoch 17/20
33333/33333 [==
          Epoch 18/20
33333/33333 [
            Epoch 19/20
33333/33333 [=
Epoch 20/20
           33333/33333 [=
            16667/16667 [-----] - 3s 199us/step
3333/33333 [-----] - 6s 193us/step
Epoch 1/40
```

# Model 1

#### **Characteristics:**

```
batch_size = 64
num_classes = 10
epochs = 50
data_augmentation = True
num_predictions = 20
```

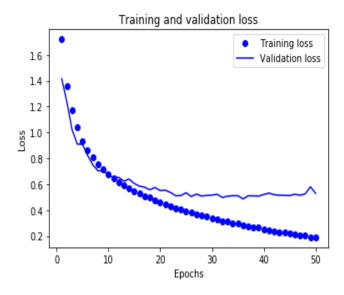
We implemented the above model using 6 layers and sgd as an optimizer.

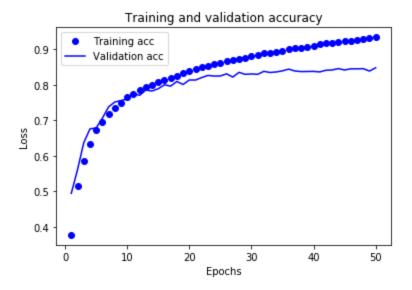
The reason behind sgd was that it does away with the redudancy of performing one updated at a time making the trainning of the model much faster.

Layer (type)	Output	Shape	Param
conv2d_1 (Conv2D)	(None,	32, 32, 32)	896
conv2d_2 (Conv2D)	(None,	32, 32, 32)	9248
batch_normalization_1 (Batch	(None,	32, 32, 32)	128
max_pooling2d_1 (MaxPooling2	(None,	32, 16, 16)	0
conv2d_3 (Conv2D)	(None,	64, 16, 16)	18496
conv2d_4 (Conv2D)	(None,	64, 16, 16)	36928
max_pooling2d_2 (MaxPooling2	(None,	64, 8, 8)	0
conv2d_5 (Conv2D)	(None,	128, 8, 8)	73856
conv2d_6 (Conv2D)	(None,	128, 8, 8)	147584
max_pooling2d_3 (MaxPooling2	(None,	128, 4, 4)	0
flatten_1 (Flatten)	(None,	2048)	0
dense_1 (Dense)	(None,	1024)	209817
dense_2 (Dense)	(None,	,	10250
Total params: 2,395,562 Trainable params: 2,395,498 Non-trainable params: 64			

```
Epoch 35/50
1563/1563 [=
                                - 28s 18ms/step - loss: 0.2946 - acc: 0.8965 - val_loss: 0.5101 - val_acc: 0.8393
                              =] - 28s 18ms/step - loss: 0.2852 - acc: 0.8998 - val_loss: 0.4856 - val_acc: 0.8442
1563/1563 [=
Epoch 37/50
1563/1563 [=
                                 29s 18ms/step - loss: 0.2700 - acc: 0.9039 - val_loss: 0.5099 - val_acc: 0.8389
Epoch 38/50
                                - 29s 18ms/step - loss: 0.2694 - acc: 0.9044 - val_loss: 0.5093 - val_acc: 0.8373
1563/1563 [====
1563/1563 [=
                   =========] - 29s 18ms/step - loss: 0.2624 - acc: 0.9075 - val_loss: 0.5073 - val_acc: 0.8375
Epoch 40/50
                                 29s 19ms/step - loss: 0.2526 - acc: 0.9097 - val_loss: 0.5203 - val_acc: 0.8378
Epoch 41/50
1563/1563 [=
                                 29s 18ms/step - loss: 0.2432 - acc: 0.9135 - val_loss: 0.5306 - val_acc: 0.8363
1563/1563 [=
                                 29s 18ms/step - loss: 0.2387 - acc: 0.9166 - val_loss: 0.5182 - val_acc: 0.8410
Epoch 43/50
                                 28s 18ms/step - loss: 0.2307 - acc: 0.9177 - val_loss: 0.5142 - val_acc: 0.8418
Epoch 44/50
                1563/1563 [=
                                 29s 18ms/step - loss: 0.2181 - acc: 0.9224 - val_loss: 0.5112 - val_acc: 0.8418
1563/1563 [=
Epoch 46/50
                                 29s 18ms/step - loss: 0.2152 - acc: 0.9234 - val_loss: 0.5223 - val_acc: 0.8450
Epoch 47/50
                   :=======] - 29s 18ms/step - loss: 0.2034 - acc: 0.9274 - val_loss: 0.5141 - val_acc: 0.8450
1563/1563 [=
1563/1563 [===
             Epoch 49/50
1563/1563 [====
            1563/1563 [===
```

Through the graph we realized that the model was overfitting due to the layers and the drop out function.





# Model 2:

### **Characteristics:**

```
batch_size = 32
num_classes = 10
epochs = 30
data_augmentation = True
```

We decreased the batch, epochs and removed the batch normalization layer while addding a dropout.

```
def base_model():
   model = Sequential()
   \label{local_model_add(Conv2D(32, (3, 3), padding='same', activation='relu', input\_shape=x\_train.shape[1:]))} \\ model.add(Dropout(0.2))
   model.add(Conv2D(32,(3,3),padding='same', activation='relu'))
   model.add(MaxPooling2D(pool_size=(2,2)))
   model.add(Conv2D(64,(3,3),padding='same',activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
   model.add(Conv2D(128,(3,3),padding='same',activation='relu'))
   # model.add(Dropout(0.2))
   \label{eq:model.add} $$ model.add(Conv2D(128,(3,3),padding='same',activation='relu')) $$ model.add(MaxPooling2D(pool\_size=(2,2))) $$ $$
   model.add(Flatten())
#model.add(Dropout(0.2))
   model.add(Dense(1024,activation='relu'))
   model.add(Dense(num_classes, activation='softmax'))
   opt = optimizers.SGD(lr=0.0008, decay=0.000, momentum=0.9, nesterov=True) # Train\ model
   model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
```

Layer (type)	Output	Shape	Param #
conv2d_7 (Conv2D)	(None,	32, 32, 32)	896
dropout_1 (Dropout)	(None,	32, 32, 32)	0
conv2d_8 (Conv2D)	(None,	32, 32, 32)	9248
max_pooling2d_4 (MaxPooling2	(None,	32, 16, 16)	0
conv2d_9 (Conv2D)	(None,	32, 16, 16)	9248
dropout_2 (Dropout)	(None,	32, 16, 16)	0
conv2d_10 (Conv2D)	(None,	64, 16, 16)	18496
max_pooling2d_5 (MaxPooling2	(None,	64, 8, 8)	0
conv2d_11 (Conv2D)	(None,	128, 8, 8)	73856
conv2d_12 (Conv2D)	(None,	128, 8, 8)	147584
max_pooling2d_6 (MaxPooling2	(None,	128, 4, 4)	0
flatten_2 (Flatten)	(None,	2048)	0
dense_3 (Dense)	(None,	1024)	2098176
dense_4 (Dense)	(None,	10)	10250

Total params: 2,367,754 Trainable params: 2,367,754 Non-trainable params: 0

```
Epoch 13/30
1563/1563 [=
    Epoch 14/30
1563/1563 [===
   Enoch 15/30
Epoch 16/30
   Epoch 17/30
Epoch 18/30
1563/1563 [============] - 24s 15ms/step - loss: 0.8164 - acc: 0.7130 - val_loss: 0.7859 - val_acc: 0.7185
Epoch 19/30
Epoch 20/30
Epoch 21/30
Epoch 22/30
     Epoch 23/30
1563/1563 [=
     =========] - 24s 15ms/step - loss: 0.6909 - acc: 0.7569 - val_loss: 0.7243 - val_acc: 0.7533
Epoch 24/30
1563/1563 [==
     Epoch 25/30
    Epoch 26/30
1563/1563 [==
    Epoch 27/30
     ==========] - 24s 15ms/step - loss: 0.6093 - acc: 0.7864 - val loss: 0.6585 - val acc: 0.7747
1563/1563 [==
Epoch 28/30
    Epoch 29/30
1563/1563 [=
     Enoch 30/30
```

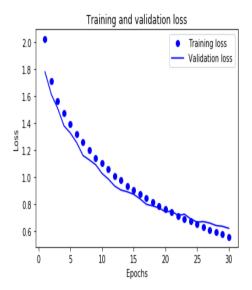
Test loss: 0.6194539049625397

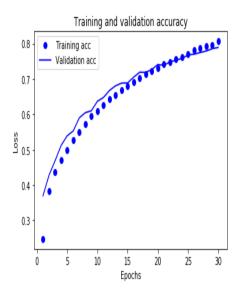
Test accuracy: 0.7892

### **Accuracy:**

Through the previous model we seen that after a certain epoch the overfitting was increasing. So we added a dropout and decreased the epochs and batch size.

With this we achieved lesser accuracy than the previous model but a better trainning and validation loss ratio and also trainning accuracy and validation accuracy.





## Model 3:

Here first we started with the base code that was given. After running 100 epochs we found out the accuracy to be around 74.82.

```
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
# initiate RMSprop optimizer
opt = keras.optimizers.rmsprop(lr=0.0001, decay=1e-6)
# Let's train the model using RMSprop
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
metrics=['accuracy'])
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
```

```
Epoch 93/100
1563/1562 [==
              Epoch 94/100
1563/1562 [===
             ==========] - 39s 25ms/step - loss: 0.7591 - acc: 0.7488 - val_loss: 0.6657 - val_acc: 0.7789
Epoch 95/100
1563/1562 [===
            ==========] - 39s 25ms/step - loss: 0.7637 - acc: 0.7486 - val_loss: 0.6637 - val_acc: 0.7861
1563/1562 [===
Epoch 97/100
1563/1562 [==
            Epoch 98/100
1563/1562 [==
                :=======] - 39s 25ms/step - loss: 0.7617 - acc: 0.7491 - val_loss: 0.6298 - val_acc: 0.7898
Epoch 99/100
Epoch 100/100
1563/1562 [============] - 39s 25ms/step - loss: 0.7690 - acc: 0.7482 - val loss: 0.6448 - val acc: 0.7847
Saved trained model at D:\NEU\CC & DNN\saved_models\keras_cifar10_trained_model.h5
10000/10000 [========
                ========= ] - 3s 272us/step
Test loss: 0.6448269945144653
Test accuracy: 0.7847
```

#### Model 4:

Now in order to increase this accuracy, various parameters needed to be changed and tried on to attain a better accuracy.

First, we started with changing the optimizer from rmsprop to adam. Because as discussed in he class by other students, adam is better at increasing the accuracy rather than rmsprop. Also here I have increased the learning rate from 0.001 to 0.002.

```
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num classes))
model.add(Activation('softmax'))
# initiate RMSprop optimizer
opt = keras.optimizers.Adamax(lr=0.002, beta_1=0.9, beta_2=0.999, epsilon=1, decay=0.0)
# Let's train the model using RMSprop
model.compile(loss='categorical_crossentropy',
       optimizer=opt,
       metrics=['accuracy'])
      Epocn 14/20
     Epoch 16/20
     1563/1562 [============] - 39s 25ms/step - loss: 1.5407 - acc: 0.4362 - val_loss: 1.4156 - val_acc: 0.4901
     Epoch 17/20
     Epoch 18/20
     1563/1562 [==
             Epoch 19/20
            1563/1562 [===
     Test loss: 1.3305378057479857
     Test accuracy: 0.5224
```

#### Model 5:

```
model.add(Flatten())
model.add(Dense(1024))
leakyrelu = keras.layers.advanced_activations.LeakyReLU(alpha=0.3)
model.add(leakyrelu)
model.add(Dropout(0.5))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))

# initiate RMSprop optimizer
opt = keras.optimizers.Adamax(lr=0.002, beta_1=0.9, beta_2=0.999, epsilon=1, decay=0.0)
```

```
Epoch 14/20
Epoch 16/20
1563/1562 [==========] - 36s 23ms/step - loss: 1.4613 - acc: 0.4703 - val_loss: 1.3308 - val_acc: 0.5228
Epoch 17/20
    1563/1562 [=
Epoch 18/20
1563/1562 [==
     Epoch 19/20
Epoch 20/20
Saved trained model at D:\NEU\CC & DNN\saved_models\keras_cifar10_trained_model.h5
10000/10000 [============ ] - 2s 211us/step
Test loss: 1.255837732887268
Test accuracy: 0.554
```

Now we tried changing the dense layer to 1024 in an attempt to try get a better accuracy and making the end layer more dense. I also replaced the ReLU function with Leaky ReLU again because it was discussed that it is better than ReLU function as it also has a small negative edge which works better with negative values.

#### Model 6:

Here I have increased the 2D convolution layers, and I now all the activation functions are Leaky ReLU. We made the convolution layers double and as result accuracy increased to 83.26 % with any sign of overfitting. The validation accuracy is 82.11%.

```
leakyrelu = keras.layers.advanced_activations.LeakyReLU(alpha=0.3)
model.add(leakyrelu)
model.add(Conv2D(conv2d, (3, 3)))
model.add(Conv2D(conv2d, (3, 3)))
model.add(leakyrelu)
model.add(leakyrelu)
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(conv2d1, (3, 3), padding='same'))
model.add(leakyrelu)
model.add(Conv2D(conv2d1, (3, 3)))
model.add(Conv2D(conv2d1, (3, 3)))
model.add(leakyrelu)
model.add(leakyrelu)
model.add(MaxPooling2D(pool_size=(2, 2)))
#model.add(Dropout(0.1
model.add(Flatten())
model.add(Dense(dense))
model.add(leakyrelu)
model.add(Dropout(dropout))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
# initiate RMSprop optimizer
opt = keras.optimizers.rmsprop(lr=0.0001, decay=1e-6)
```

```
s/step - 1055. 0.310/ - acc. 0.0223 - vai 1055. 0.330/
Epoch 43/50
    Epoch 44/50
    1563/1562 [=
Epoch 46/50
1563/1562 [=:
    Epoch 48/50
1563/1562 [=
      ==========] - 55s 35ms/step - loss: 0.4877 - acc: 0.8333 - val_loss: 0.5083 - val_acc: 0.8293
1563/1562 [============] - 90s 57ms/step - loss: 0.4862 - acc: 0.8326 - val_loss: 0.5238 - val_acc: 0.8211
```

### Model 7:

Here we have increased the number of epochs of 100 and I have kept everything the same as observation 4. This is our best accuracy found from all our observations. 85.54%

```
batch_size = 32
num_classes = 10
epochs = 100
num_predictions = 20
conv2d=32
conv2d1=64
verbose=1
input_shape= 784
data_augmentation = True
dense=512
dropout=0.2
```

```
model_name = 'keras_cifar10_trained_model.h5'
# The data, shuffled and split between train and test sets:
(x_{train}, y_{train}), (x_{test}, y_{test}) = cifar10.load_data()
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
# Convert class vectors to binary class matrices.
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
model = Sequential()
model.add(Conv2D(conv2d, (3, 3), padding='same'
            input shape=x train.shape[1:]))
leakyrelu = keras.layers.advanced_activations.LeakyReLU(alpha=0.3)
model.add(leakvrelu)
model.add(Conv2D(conv2d, (3, 3)))
model.add(leakyrelu)
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(conv2d1, (3, 3), padding='same'))
model.add(leakyrelu)
model.add(Conv2D(conv2d1, (3, 3)))
model.add(leakyrelu)
model.add(MaxPooling2D(pool_size=(2, 2)))
#model.add(Dropout(0.1))
model.add(Flatten())
model.add(Dense(dense))
model.add(leakyrelu)
model.add(Dropout(dropout))
model.add(Dense(num_classes))
model.add(Activation('softmax'))
# initiate RMSprop optimizer
opt = keras.optimizers.rmsprop(lr=0.0001, decay=1e-6)
        Epoch 94/100
                   1563/1562 [===
        Epoch 95/100
        1563/1562 [===
                    Epoch 96/100
        1563/1562 [===
                    Epoch 97/100
        1563/1562 [==
                       =========] - 40s 25ms/step - loss: 0.4226 - acc: 0.8549 - val_loss: 0.4727 - val_acc: 0.8438
        Epoch 98/100
        1563/1562 [==
                      Epoch 99/100
                   1563/1562 [====
        Epoch 100/100
        _____
        ValueError
                                   Traceback (most recent call last)
        <ipython-input-1-6af073ed1e9f> in <module>()
```

# **Conclusion:**

We achieved the best acuraccy in Model 7 with 85.54% by tweaking the hyperparameters and layers. From the previous task and the new task we derived the best model with leaky relu.