

Import Req Lib

```
In [1]: %matplotlib inline

import shutil
import random
import numpy as np
from warnings import filterwarnings
filterwarnings('ignore')

from tensorflow.keras import layers, regularizers, optimizers
from tensorflow.keras import models
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import LeakyReLU, Dense, Activation, Flatten, Dropout, BatchNormalization, Conv2D, MaxPooling2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import tensorflow as tf

import os
import time
import csv

from matplotlib import figure
```

Define 3 worker

```
In [2]: # Set the number of threads
number_of_worker = 3
os.environ['OMP_NUM_THREADS'] = '3' # OpenMP threads for parallelism
os.environ['TF_NUM_INTEROP_THREADS'] = '3' # Threads for inter-operation parallelism
os.environ['TF_NUM_INTRAOP_THREADS'] = '3' # Threads for intra-operation parallelism

# Confirm TensorFlow is using the specified number of threads
tf.config.threading.set_inter_op_parallelism_threads(number_of_worker)
tf.config.threading.set_intra_op_parallelism_threads(number_of_worker)
```

Train Val data Split

```
In [3]: source_dir = r"C:\Users\nikhi\OneDrive\Desktop\Final Project\DATA\Convert_Audio_File_to_jpg_file"
target_dir = r'genres_train_val_split_data'
split_ratio = 0.8

def Train_Test_Split(source_dir, target_dir, split_ratio):
    # Define source and target directories
    train_dir = os.path.join(target_dir, 'train')
    val_dir = os.path.join(target_dir, 'val')

    # Create target directories if they don't exist
    os.makedirs(train_dir, exist_ok=True)
    os.makedirs(val_dir, exist_ok=True)

    # Get the list of class directories
    classes = [d for d in os.listdir(source_dir) if os.path.isdir(os.path.join(source_dir, d))]

    for class_name in classes:
        # Create class directories in train and val folders
        os.makedirs(os.path.join(train_dir, class_name), exist_ok=True)
        os.makedirs(os.path.join(val_dir, class_name), exist_ok=True)

        # Get list of images in the class directory
        class_dir = os.path.join(source_dir, class_name)
        images = [f for f in os.listdir(class_dir) if os.path.isfile(os.path.join(class_dir, f))]

        # Shuffle the images
        random.shuffle(images)

        # Compute the split point
        split_point = int(len(images) * split_ratio)

        # Split the images into training and validation sets
        train_images = images[:split_point]
        val_images = images[split_point:]
```

```

# Move the images to the respective directories
for img in train_images:
    shutil.copy(os.path.join(class_dir, img), os.path.join(train_dir, class_name, img))

for img in val_images:
    shutil.copy(os.path.join(class_dir, img), os.path.join(val_dir, class_name, img))

print("Data split completed successfully!")

```

In [4]: `Train_Test_Split(source_dir,target_dir,split_ratio)`

Data split completed successfully!

Load the Data

```

In [5]: WIDTH = 64
HEIGHT = 64
BATCH_SIZE = 32
TRAIN_DIR=r'genres_train_val_split_data/train'
val_dir = r'genres_train_val_split_data/val'

# data prep
train_datagen = ImageDataGenerator(
    rescale=1./255.,validation_split=0.25)

train_generator = train_datagen.flow_from_directory(
    TRAIN_DIR,
    target_size=(HEIGHT, WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical')

validation_gen = train_datagen.flow_from_directory(
    val_dir,target_size = (HEIGHT,WIDTH),
    batch_size = BATCH_SIZE,
    class_mode = 'categorical'
)

```

Found 800 images belonging to 10 classes.

Found 200 images belonging to 10 classes.

Model Architecture

```

In [6]: model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same',
    input_shape=(64,64,3)))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))
model.add(Conv2D(128, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(128, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer=RMSprop(learning_rate=0.0005, decay=1e-6),loss="categorical_crossentropy",metrics=["accuracy"])
model.summary()

```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|--------------------------------|---------------------|-----------|
| conv2d (Conv2D) | (None, 64, 64, 32) | 896 |
| activation (Activation) | (None, 64, 64, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 62, 62, 64) | 18,496 |
| activation_1 (Activation) | (None, 62, 62, 64) | 0 |
| max_pooling2d (MaxPooling2D) | (None, 31, 31, 64) | 0 |
| dropout (Dropout) | (None, 31, 31, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 31, 31, 64) | 36,928 |
| activation_2 (Activation) | (None, 31, 31, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 29, 29, 64) | 36,928 |
| activation_3 (Activation) | (None, 29, 29, 64) | 0 |
| max_pooling2d_1 (MaxPooling2D) | (None, 14, 14, 64) | 0 |
| dropout_1 (Dropout) | (None, 14, 14, 64) | 0 |
| conv2d_4 (Conv2D) | (None, 14, 14, 128) | 73,856 |
| activation_4 (Activation) | (None, 14, 14, 128) | 0 |
| conv2d_5 (Conv2D) | (None, 12, 12, 128) | 147,584 |
| activation_5 (Activation) | (None, 12, 12, 128) | 0 |
| max_pooling2d_2 (MaxPooling2D) | (None, 6, 6, 128) | 0 |
| dropout_2 (Dropout) | (None, 6, 6, 128) | 0 |
| flatten (Flatten) | (None, 4608) | 0 |
| dense (Dense) | (None, 512) | 2,359,808 |
| activation_6 (Activation) | (None, 512) | 0 |
| dropout_3 (Dropout) | (None, 512) | 0 |
| dense_1 (Dense) | (None, 10) | 5,130 |

Total params: 2,679,626 (10.22 MB)

Trainable params: 2,679,626 (10.22 MB)

Non-trainable params: 0 (0.00 B)

```
In [7]: STEP_SIZE_TRAIN=train_generator.n//train_generator.batch_size
# Measure the execution time
start_time = time.time()

model.fit(train_generator,validation_data=validation_gen,epochs=200)

end_time = time.time()
elapsed_time = end_time - start_time
```

[illegible]

| | | | | | | | |
|--------------|-------|-----|------------|--------------------|----------------|------------------------|--------------------|
| Epoch 42/200 | 25/25 | 11s | 438ms/step | - accuracy: 0.7672 | - loss: 0.7296 | - val_accuracy: 0.4550 | - val_loss: 1.7125 |
| Epoch 43/200 | 25/25 | 11s | 445ms/step | - accuracy: 0.7301 | - loss: 0.7281 | - val_accuracy: 0.4950 | - val_loss: 1.5391 |
| Epoch 44/200 | 25/25 | 11s | 458ms/step | - accuracy: 0.7694 | - loss: 0.6188 | - val_accuracy: 0.5400 | - val_loss: 1.4922 |
| Epoch 45/200 | 25/25 | 11s | 451ms/step | - accuracy: 0.7854 | - loss: 0.6459 | - val_accuracy: 0.5050 | - val_loss: 1.6969 |
| Epoch 46/200 | 25/25 | 13s | 502ms/step | - accuracy: 0.7587 | - loss: 0.7253 | - val_accuracy: 0.5800 | - val_loss: 1.4690 |
| Epoch 47/200 | 25/25 | 12s | 486ms/step | - accuracy: 0.8226 | - loss: 0.5347 | - val_accuracy: 0.5500 | - val_loss: 1.4696 |
| Epoch 48/200 | 25/25 | 12s | 494ms/step | - accuracy: 0.8037 | - loss: 0.5382 | - val_accuracy: 0.5500 | - val_loss: 1.4454 |
| Epoch 49/200 | 25/25 | 12s | 464ms/step | - accuracy: 0.8286 | - loss: 0.4913 | - val_accuracy: 0.5650 | - val_loss: 1.3963 |
| Epoch 50/200 | 25/25 | 10s | 408ms/step | - accuracy: 0.8572 | - loss: 0.4218 | - val_accuracy: 0.5700 | - val_loss: 1.5492 |
| Epoch 51/200 | 25/25 | 11s | 439ms/step | - accuracy: 0.8326 | - loss: 0.4634 | - val_accuracy: 0.5250 | - val_loss: 1.8723 |
| Epoch 52/200 | 25/25 | 12s | 462ms/step | - accuracy: 0.8203 | - loss: 0.5689 | - val_accuracy: 0.5500 | - val_loss: 1.6347 |
| Epoch 53/200 | 25/25 | 13s | 499ms/step | - accuracy: 0.8558 | - loss: 0.4413 | - val_accuracy: 0.5250 | - val_loss: 1.7110 |
| Epoch 54/200 | 25/25 | 13s | 517ms/step | - accuracy: 0.8577 | - loss: 0.4649 | - val_accuracy: 0.5750 | - val_loss: 1.5534 |
| Epoch 55/200 | 25/25 | 13s | 510ms/step | - accuracy: 0.8622 | - loss: 0.3862 | - val_accuracy: 0.5800 | - val_loss: 1.4429 |
| Epoch 56/200 | 25/25 | 13s | 500ms/step | - accuracy: 0.8415 | - loss: 0.4130 | - val_accuracy: 0.5600 | - val_loss: 1.6298 |
| Epoch 57/200 | 25/25 | 12s | 473ms/step | - accuracy: 0.8331 | - loss: 0.4591 | - val_accuracy: 0.5550 | - val_loss: 1.7618 |
| Epoch 58/200 | 25/25 | 13s | 512ms/step | - accuracy: 0.8447 | - loss: 0.4063 | - val_accuracy: 0.5600 | - val_loss: 1.7022 |
| Epoch 59/200 | 25/25 | 13s | 497ms/step | - accuracy: 0.8745 | - loss: 0.3720 | - val_accuracy: 0.5500 | - val_loss: 1.7594 |
| Epoch 60/200 | 25/25 | 12s | 484ms/step | - accuracy: 0.8637 | - loss: 0.3368 | - val_accuracy: 0.5600 | - val_loss: 1.4790 |
| Epoch 61/200 | 25/25 | 12s | 458ms/step | - accuracy: 0.9153 | - loss: 0.2569 | - val_accuracy: 0.5450 | - val_loss: 1.6113 |
| Epoch 62/200 | 25/25 | 12s | 471ms/step | - accuracy: 0.9336 | - loss: 0.2270 | - val_accuracy: 0.5000 | - val_loss: 2.4138 |
| Epoch 63/200 | 25/25 | 11s | 418ms/step | - accuracy: 0.9275 | - loss: 0.2432 | - val_accuracy: 0.5550 | - val_loss: 2.1046 |
| Epoch 64/200 | 25/25 | 11s | 426ms/step | - accuracy: 0.9020 | - loss: 0.2548 | - val_accuracy: 0.5650 | - val_loss: 1.9601 |
| Epoch 65/200 | 25/25 | 11s | 445ms/step | - accuracy: 0.9056 | - loss: 0.2923 | - val_accuracy: 0.6000 | - val_loss: 1.7826 |
| Epoch 66/200 | 25/25 | 11s | 419ms/step | - accuracy: 0.9148 | - loss: 0.2506 | - val_accuracy: 0.5550 | - val_loss: 1.8186 |
| Epoch 67/200 | 25/25 | 11s | 441ms/step | - accuracy: 0.9171 | - loss: 0.2525 | - val_accuracy: 0.5900 | - val_loss: 1.8137 |
| Epoch 68/200 | 25/25 | 11s | 447ms/step | - accuracy: 0.9299 | - loss: 0.2053 | - val_accuracy: 0.5550 | - val_loss: 2.3692 |
| Epoch 69/200 | 25/25 | 11s | 448ms/step | - accuracy: 0.9197 | - loss: 0.2721 | - val_accuracy: 0.5500 | - val_loss: 2.1923 |
| Epoch 70/200 | 25/25 | 12s | 459ms/step | - accuracy: 0.9512 | - loss: 0.1595 | - val_accuracy: 0.5800 | - val_loss: 2.3808 |
| Epoch 71/200 | 25/25 | 12s | 480ms/step | - accuracy: 0.9184 | - loss: 0.2301 | - val_accuracy: 0.5500 | - val_loss: 2.0233 |
| Epoch 72/200 | 25/25 | 13s | 522ms/step | - accuracy: 0.9068 | - loss: 0.2479 | - val_accuracy: 0.5700 | - val_loss: 2.1736 |
| Epoch 73/200 | 25/25 | 12s | 479ms/step | - accuracy: 0.9345 | - loss: 0.1671 | - val_accuracy: 0.5800 | - val_loss: 1.8012 |
| Epoch 74/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9508 | - loss: 0.1823 | - val_accuracy: 0.5800 | - val_loss: 1.9842 |
| Epoch 75/200 | 25/25 | 11s | 450ms/step | - accuracy: 0.9300 | - loss: 0.2190 | - val_accuracy: 0.5750 | - val_loss: 2.5367 |
| Epoch 76/200 | 25/25 | 12s | 464ms/step | - accuracy: 0.9385 | - loss: 0.1612 | - val_accuracy: 0.5600 | - val_loss: 2.3644 |
| Epoch 77/200 | 25/25 | 12s | 486ms/step | - accuracy: 0.9416 | - loss: 0.1744 | - val_accuracy: 0.6050 | - val_loss: 2.2238 |
| Epoch 78/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9580 | - loss: 0.1393 | - val_accuracy: 0.5850 | - val_loss: 2.2327 |
| Epoch 79/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9435 | - loss: 0.1561 | - val_accuracy: 0.6100 | - val_loss: 2.2643 |
| Epoch 80/200 | 25/25 | 12s | 475ms/step | - accuracy: 0.9536 | - loss: 0.1949 | - val_accuracy: 0.5950 | - val_loss: 2.2301 |
| Epoch 81/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9532 | - loss: 0.1703 | - val_accuracy: 0.5700 | - val_loss: 2.2645 |
| Epoch 82/200 | 25/25 | 11s | 459ms/step | - accuracy: 0.9617 | - loss: 0.0973 | - val_accuracy: 0.5700 | - val_loss: 2.4140 |

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|---------------|-------|-----|------------|--------------------|----------------|------------------------|--------------------|
| Epoch 83/200 | 25/25 | 11s | 450ms/step | - accuracy: 0.9347 | - loss: 0.1793 | - val_accuracy: 0.5800 | - val_loss: 2.2786 |
| Epoch 84/200 | 25/25 | 11s | 449ms/step | - accuracy: 0.9474 | - loss: 0.1033 | - val_accuracy: 0.5750 | - val_loss: 2.3670 |
| Epoch 85/200 | 25/25 | 11s | 453ms/step | - accuracy: 0.9548 | - loss: 0.1371 | - val_accuracy: 0.5600 | - val_loss: 2.4043 |
| Epoch 86/200 | 25/25 | 11s | 455ms/step | - accuracy: 0.9691 | - loss: 0.0769 | - val_accuracy: 0.5900 | - val_loss: 2.4306 |
| Epoch 87/200 | 25/25 | 13s | 509ms/step | - accuracy: 0.9638 | - loss: 0.1350 | - val_accuracy: 0.5850 | - val_loss: 2.1009 |
| Epoch 88/200 | 25/25 | 13s | 520ms/step | - accuracy: 0.9666 | - loss: 0.0947 | - val_accuracy: 0.5700 | - val_loss: 2.6385 |
| Epoch 89/200 | 25/25 | 12s | 463ms/step | - accuracy: 0.9648 | - loss: 0.1116 | - val_accuracy: 0.5850 | - val_loss: 2.4659 |
| Epoch 90/200 | 25/25 | 12s | 472ms/step | - accuracy: 0.9513 | - loss: 0.1856 | - val_accuracy: 0.6000 | - val_loss: 2.4104 |
| Epoch 91/200 | 25/25 | 12s | 478ms/step | - accuracy: 0.9636 | - loss: 0.1290 | - val_accuracy: 0.6000 | - val_loss: 2.7544 |
| Epoch 92/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9492 | - loss: 0.1673 | - val_accuracy: 0.5850 | - val_loss: 2.5110 |
| Epoch 93/200 | 25/25 | 12s | 458ms/step | - accuracy: 0.9847 | - loss: 0.0773 | - val_accuracy: 0.5650 | - val_loss: 2.4438 |
| Epoch 94/200 | 25/25 | 11s | 446ms/step | - accuracy: 0.9749 | - loss: 0.0914 | - val_accuracy: 0.5900 | - val_loss: 2.8167 |
| Epoch 95/200 | 25/25 | 12s | 463ms/step | - accuracy: 0.9696 | - loss: 0.0948 | - val_accuracy: 0.5450 | - val_loss: 2.9110 |
| Epoch 96/200 | 25/25 | 12s | 485ms/step | - accuracy: 0.9595 | - loss: 0.1383 | - val_accuracy: 0.5800 | - val_loss: 2.2549 |
| Epoch 97/200 | 25/25 | 20s | 463ms/step | - accuracy: 0.9758 | - loss: 0.0668 | - val_accuracy: 0.5550 | - val_loss: 2.1897 |
| Epoch 98/200 | 25/25 | 11s | 458ms/step | - accuracy: 0.9547 | - loss: 0.1388 | - val_accuracy: 0.5750 | - val_loss: 2.3984 |
| Epoch 99/200 | 25/25 | 11s | 452ms/step | - accuracy: 0.9875 | - loss: 0.0453 | - val_accuracy: 0.5850 | - val_loss: 2.7185 |
| Epoch 100/200 | 25/25 | 12s | 470ms/step | - accuracy: 0.9522 | - loss: 0.1185 | - val_accuracy: 0.5650 | - val_loss: 2.8550 |
| Epoch 101/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9707 | - loss: 0.0789 | - val_accuracy: 0.5600 | - val_loss: 2.9188 |
| Epoch 102/200 | 25/25 | 11s | 453ms/step | - accuracy: 0.9429 | - loss: 0.1708 | - val_accuracy: 0.5800 | - val_loss: 2.5333 |
| Epoch 103/200 | 25/25 | 12s | 460ms/step | - accuracy: 0.9541 | - loss: 0.1467 | - val_accuracy: 0.5650 | - val_loss: 2.8877 |
| Epoch 104/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9750 | - loss: 0.0700 | - val_accuracy: 0.5700 | - val_loss: 2.9475 |
| Epoch 105/200 | 25/25 | 11s | 453ms/step | - accuracy: 0.9723 | - loss: 0.0933 | - val_accuracy: 0.5550 | - val_loss: 2.5764 |
| Epoch 106/200 | 25/25 | 11s | 451ms/step | - accuracy: 0.9811 | - loss: 0.0727 | - val_accuracy: 0.5650 | - val_loss: 2.3499 |
| Epoch 107/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9667 | - loss: 0.0938 | - val_accuracy: 0.5650 | - val_loss: 3.0872 |
| Epoch 108/200 | 25/25 | 11s | 436ms/step | - accuracy: 0.9589 | - loss: 0.1414 | - val_accuracy: 0.5950 | - val_loss: 3.2135 |
| Epoch 109/200 | 25/25 | 11s | 445ms/step | - accuracy: 0.9679 | - loss: 0.1062 | - val_accuracy: 0.5700 | - val_loss: 2.9951 |
| Epoch 110/200 | 25/25 | 11s | 451ms/step | - accuracy: 0.9856 | - loss: 0.0488 | - val_accuracy: 0.5850 | - val_loss: 3.3977 |
| Epoch 111/200 | 25/25 | 11s | 436ms/step | - accuracy: 0.9446 | - loss: 0.1606 | - val_accuracy: 0.5650 | - val_loss: 3.1326 |
| Epoch 112/200 | 25/25 | 12s | 476ms/step | - accuracy: 0.9832 | - loss: 0.0424 | - val_accuracy: 0.5650 | - val_loss: 2.7708 |
| Epoch 113/200 | 25/25 | 11s | 451ms/step | - accuracy: 0.9500 | - loss: 0.1129 | - val_accuracy: 0.5750 | - val_loss: 2.9067 |
| Epoch 114/200 | 25/25 | 12s | 475ms/step | - accuracy: 0.9897 | - loss: 0.0355 | - val_accuracy: 0.5950 | - val_loss: 2.9419 |
| Epoch 115/200 | 25/25 | 11s | 446ms/step | - accuracy: 0.9769 | - loss: 0.0644 | - val_accuracy: 0.5600 | - val_loss: 3.7960 |
| Epoch 116/200 | 25/25 | 11s | 456ms/step | - accuracy: 0.9770 | - loss: 0.0871 | - val_accuracy: 0.5700 | - val_loss: 3.1759 |
| Epoch 117/200 | 25/25 | 12s | 459ms/step | - accuracy: 0.9854 | - loss: 0.0627 | - val_accuracy: 0.5700 | - val_loss: 3.0052 |
| Epoch 118/200 | 25/25 | 12s | 459ms/step | - accuracy: 0.9806 | - loss: 0.0613 | - val_accuracy: 0.5750 | - val_loss: 3.2695 |
| Epoch 119/200 | 25/25 | 11s | 446ms/step | - accuracy: 0.9679 | - loss: 0.1012 | - val_accuracy: 0.5650 | - val_loss: 2.8748 |
| Epoch 120/200 | 25/25 | 11s | 441ms/step | - accuracy: 0.9692 | - loss: 0.0690 | - val_accuracy: 0.6050 | - val_loss: 2.5103 |
| Epoch 121/200 | 25/25 | 11s | 440ms/step | - accuracy: 0.9825 | - loss: 0.0566 | - val_accuracy: 0.6000 | - val_loss: 2.9525 |
| Epoch 122/200 | 25/25 | 21s | 467ms/step | - accuracy: 0.9866 | - loss: 0.0416 | - val_accuracy: 0.5750 | - val_loss: 3.5913 |
| Epoch 123/200 | 25/25 | 13s | 506ms/step | - accuracy: 0.9780 | - loss: 0.1305 | - val_accuracy: 0.5700 | - val_loss: 2.7642 |

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| Epoch 124/200 | 25/25 | 13s | 500ms/step | - accuracy: 0.9718 | - loss: 0.0886 | - val_accuracy: 0.5750 | - val_loss: 3.1585 |
| Epoch 125/200 | 25/25 | 12s | 458ms/step | - accuracy: 0.9804 | - loss: 0.0619 | - val_accuracy: 0.5650 | - val_loss: 2.9625 |
| Epoch 126/200 | 25/25 | 12s | 461ms/step | - accuracy: 0.9762 | - loss: 0.0649 | - val_accuracy: 0.5750 | - val_loss: 3.0198 |
| Epoch 127/200 | 25/25 | 11s | 448ms/step | - accuracy: 0.9707 | - loss: 0.1140 | - val_accuracy: 0.5750 | - val_loss: 2.7649 |
| Epoch 128/200 | 25/25 | 11s | 425ms/step | - accuracy: 0.9731 | - loss: 0.0610 | - val_accuracy: 0.6200 | - val_loss: 2.5508 |
| Epoch 129/200 | 25/25 | 11s | 441ms/step | - accuracy: 0.9855 | - loss: 0.0462 | - val_accuracy: 0.5600 | - val_loss: 3.7263 |
| Epoch 130/200 | 25/25 | 11s | 431ms/step | - accuracy: 0.9819 | - loss: 0.0629 | - val_accuracy: 0.5700 | - val_loss: 3.2173 |
| Epoch 131/200 | 25/25 | 11s | 431ms/step | - accuracy: 0.9690 | - loss: 0.0907 | - val_accuracy: 0.5850 | - val_loss: 3.3084 |
| Epoch 132/200 | 25/25 | 11s | 444ms/step | - accuracy: 0.9616 | - loss: 0.0969 | - val_accuracy: 0.5950 | - val_loss: 2.6866 |
| Epoch 133/200 | 25/25 | 12s | 462ms/step | - accuracy: 0.9888 | - loss: 0.0369 | - val_accuracy: 0.5950 | - val_loss: 2.8829 |
| Epoch 134/200 | 25/25 | 11s | 447ms/step | - accuracy: 0.9853 | - loss: 0.0488 | - val_accuracy: 0.5750 | - val_loss: 2.7760 |
| Epoch 135/200 | 25/25 | 12s | 469ms/step | - accuracy: 0.9835 | - loss: 0.0482 | - val_accuracy: 0.5650 | - val_loss: 3.7458 |
| Epoch 136/200 | 25/25 | 12s | 472ms/step | - accuracy: 0.9735 | - loss: 0.0852 | - val_accuracy: 0.5800 | - val_loss: 2.7073 |
| Epoch 137/200 | 25/25 | 12s | 484ms/step | - accuracy: 0.9857 | - loss: 0.0469 | - val_accuracy: 0.5500 | - val_loss: 3.1712 |
| Epoch 138/200 | 25/25 | 12s | 481ms/step | - accuracy: 0.9869 | - loss: 0.0471 | - val_accuracy: 0.5950 | - val_loss: 2.9931 |
| Epoch 139/200 | 25/25 | 12s | 495ms/step | - accuracy: 0.9815 | - loss: 0.0554 | - val_accuracy: 0.5850 | - val_loss: 2.8937 |
| Epoch 140/200 | 25/25 | 12s | 484ms/step | - accuracy: 0.9905 | - loss: 0.0404 | - val_accuracy: 0.5650 | - val_loss: 3.5348 |
| Epoch 141/200 | 25/25 | 12s | 474ms/step | - accuracy: 0.9711 | - loss: 0.1107 | - val_accuracy: 0.5450 | - val_loss: 2.9330 |
| Epoch 142/200 | 25/25 | 11s | 456ms/step | - accuracy: 0.9827 | - loss: 0.0638 | - val_accuracy: 0.5800 | - val_loss: 2.7175 |
| Epoch 143/200 | 25/25 | 11s | 453ms/step | - accuracy: 0.9693 | - loss: 0.1044 | - val_accuracy: 0.5900 | - val_loss: 2.5806 |
| Epoch 144/200 | 25/25 | 12s | 462ms/step | - accuracy: 0.9912 | - loss: 0.0224 | - val_accuracy: 0.5650 | - val_loss: 3.2506 |
| Epoch 145/200 | 25/25 | 12s | 459ms/step | - accuracy: 0.9614 | - loss: 0.1111 | - val_accuracy: 0.5550 | - val_loss: 3.4666 |
| Epoch 146/200 | 25/25 | 11s | 456ms/step | - accuracy: 0.9848 | - loss: 0.0526 | - val_accuracy: 0.5650 | - val_loss: 3.5513 |
| Epoch 147/200 | 25/25 | 12s | 474ms/step | - accuracy: 0.9844 | - loss: 0.0788 | - val_accuracy: 0.5750 | - val_loss: 2.8310 |
| Epoch 148/200 | 25/25 | 11s | 441ms/step | - accuracy: 0.9880 | - loss: 0.0294 | - val_accuracy: 0.6150 | - val_loss: 3.0327 |
| Epoch 149/200 | 25/25 | 12s | 463ms/step | - accuracy: 0.9798 | - loss: 0.0653 | - val_accuracy: 0.6100 | - val_loss: 2.5929 |
| Epoch 150/200 | 25/25 | 12s | 465ms/step | - accuracy: 0.9912 | - loss: 0.0427 | - val_accuracy: 0.5750 | - val_loss: 3.6527 |
| Epoch 151/200 | 25/25 | 12s | 464ms/step | - accuracy: 0.9785 | - loss: 0.1017 | - val_accuracy: 0.5600 | - val_loss: 3.2230 |
| Epoch 152/200 | 25/25 | 12s | 466ms/step | - accuracy: 0.9716 | - loss: 0.0848 | - val_accuracy: 0.5850 | - val_loss: 3.4565 |
| Epoch 153/200 | 25/25 | 11s | 452ms/step | - accuracy: 0.9892 | - loss: 0.0360 | - val_accuracy: 0.5800 | - val_loss: 3.7426 |
| Epoch 154/200 | 25/25 | 12s | 486ms/step | - accuracy: 0.9900 | - loss: 0.0370 | - val_accuracy: 0.5850 | - val_loss: 3.6133 |
| Epoch 155/200 | 25/25 | 12s | 475ms/step | - accuracy: 0.9752 | - loss: 0.0612 | - val_accuracy: 0.5850 | - val_loss: 3.4285 |
| Epoch 156/200 | 25/25 | 12s | 476ms/step | - accuracy: 0.9927 | - loss: 0.0228 | - val_accuracy: 0.5850 | - val_loss: 3.9586 |
| Epoch 157/200 | 25/25 | 12s | 487ms/step | - accuracy: 0.9683 | - loss: 0.1098 | - val_accuracy: 0.5600 | - val_loss: 3.3739 |
| Epoch 158/200 | 25/25 | 11s | 453ms/step | - accuracy: 0.9795 | - loss: 0.0823 | - val_accuracy: 0.5700 | - val_loss: 3.5236 |
| Epoch 159/200 | 25/25 | 12s | 470ms/step | - accuracy: 0.9853 | - loss: 0.0560 | - val_accuracy: 0.5550 | - val_loss: 3.9693 |
| Epoch 160/200 | 25/25 | 13s | 507ms/step | - accuracy: 0.9642 | - loss: 0.1503 | - val_accuracy: 0.5900 | - val_loss: 3.8540 |
| Epoch 161/200 | 25/25 | 12s | 473ms/step | - accuracy: 0.9885 | - loss: 0.0555 | - val_accuracy: 0.5750 | - val_loss: 3.8009 |
| Epoch 162/200 | 25/25 | 12s | 477ms/step | - accuracy: 0.9780 | - loss: 0.0851 | - val_accuracy: 0.6000 | - val_loss: 3.0384 |
| Epoch 163/200 | 25/25 | 12s | 491ms/step | - accuracy: 0.9875 | - loss: 0.0423 | - val_accuracy: 0.6050 | - val_loss: 3.1324 |
| Epoch 164/200 | 25/25 | 12s | 472ms/step | - accuracy: 0.9842 | - loss: 0.0422 | - val_accuracy: 0.5850 | - val_loss: 3.5753 |


```

Epoch 165/200
25/25 ----- 13s 509ms/step - accuracy: 0.9946 - loss: 0.0276 - val_accuracy: 0.5800 - val_loss: 4.1496
Epoch 166/200
25/25 ----- 12s 475ms/step - accuracy: 0.9832 - loss: 0.0464 - val_accuracy: 0.5450 - val_loss: 3.8821
Epoch 167/200
25/25 ----- 13s 500ms/step - accuracy: 0.9846 - loss: 0.0371 - val_accuracy: 0.5700 - val_loss: 4.1487
Epoch 168/200
25/25 ----- 12s 498ms/step - accuracy: 0.9689 - loss: 0.1025 - val_accuracy: 0.5750 - val_loss: 3.4159
Epoch 169/200
25/25 ----- 12s 481ms/step - accuracy: 0.9792 - loss: 0.0696 - val_accuracy: 0.5800 - val_loss: 3.8318
Epoch 170/200
25/25 ----- 12s 474ms/step - accuracy: 0.9868 - loss: 0.0269 - val_accuracy: 0.5700 - val_loss: 3.6744
Epoch 171/200
25/25 ----- 20s 456ms/step - accuracy: 0.9849 - loss: 0.0440 - val_accuracy: 0.5550 - val_loss: 3.8352
Epoch 172/200
25/25 ----- 12s 463ms/step - accuracy: 0.9948 - loss: 0.0249 - val_accuracy: 0.5500 - val_loss: 4.1566
Epoch 173/200
25/25 ----- 13s 528ms/step - accuracy: 0.9784 - loss: 0.0598 - val_accuracy: 0.5800 - val_loss: 4.4257
Epoch 174/200
25/25 ----- 20s 489ms/step - accuracy: 0.9742 - loss: 0.0952 - val_accuracy: 0.5450 - val_loss: 4.0259
Epoch 175/200
25/25 ----- 12s 472ms/step - accuracy: 0.9933 - loss: 0.0179 - val_accuracy: 0.5750 - val_loss: 3.7908
Epoch 176/200
25/25 ----- 12s 475ms/step - accuracy: 0.9774 - loss: 0.1114 - val_accuracy: 0.5750 - val_loss: 3.6599
Epoch 177/200
25/25 ----- 12s 466ms/step - accuracy: 0.9853 - loss: 0.0346 - val_accuracy: 0.5600 - val_loss: 4.2077
Epoch 178/200
25/25 ----- 12s 475ms/step - accuracy: 0.9845 - loss: 0.0378 - val_accuracy: 0.5700 - val_loss: 4.1975
Epoch 179/200
25/25 ----- 12s 477ms/step - accuracy: 0.9792 - loss: 0.0861 - val_accuracy: 0.5750 - val_loss: 4.6767
Epoch 180/200
25/25 ----- 12s 481ms/step - accuracy: 0.9858 - loss: 0.0325 - val_accuracy: 0.5700 - val_loss: 4.3123
Epoch 181/200
25/25 ----- 12s 484ms/step - accuracy: 0.9795 - loss: 0.0905 - val_accuracy: 0.5850 - val_loss: 4.3368
Epoch 182/200
25/25 ----- 11s 446ms/step - accuracy: 0.9910 - loss: 0.0388 - val_accuracy: 0.6150 - val_loss: 4.0462
Epoch 183/200
25/25 ----- 11s 452ms/step - accuracy: 0.9808 - loss: 0.0731 - val_accuracy: 0.6000 - val_loss: 3.6067
Epoch 184/200
25/25 ----- 12s 465ms/step - accuracy: 0.9906 - loss: 0.0207 - val_accuracy: 0.5900 - val_loss: 4.4340
Epoch 185/200
25/25 ----- 11s 453ms/step - accuracy: 0.9866 - loss: 0.0524 - val_accuracy: 0.5950 - val_loss: 4.0456
Epoch 186/200
25/25 ----- 11s 435ms/step - accuracy: 0.9843 - loss: 0.0646 - val_accuracy: 0.6100 - val_loss: 3.4074
Epoch 187/200
25/25 ----- 11s 434ms/step - accuracy: 0.9754 - loss: 0.0781 - val_accuracy: 0.5750 - val_loss: 3.6424
Epoch 188/200
25/25 ----- 11s 435ms/step - accuracy: 0.9921 - loss: 0.0286 - val_accuracy: 0.5900 - val_loss: 3.4255
Epoch 189/200
25/25 ----- 11s 458ms/step - accuracy: 0.9945 - loss: 0.0156 - val_accuracy: 0.6150 - val_loss: 3.5043
Epoch 190/200
25/25 ----- 11s 457ms/step - accuracy: 0.9765 - loss: 0.0669 - val_accuracy: 0.5900 - val_loss: 3.0471
Epoch 191/200
25/25 ----- 11s 441ms/step - accuracy: 0.9822 - loss: 0.0497 - val_accuracy: 0.5900 - val_loss: 3.5785
Epoch 192/200
25/25 ----- 11s 432ms/step - accuracy: 0.9866 - loss: 0.0376 - val_accuracy: 0.6000 - val_loss: 3.5430
Epoch 193/200
25/25 ----- 11s 447ms/step - accuracy: 0.9905 - loss: 0.0331 - val_accuracy: 0.5700 - val_loss: 3.9939
Epoch 194/200
25/25 ----- 21s 459ms/step - accuracy: 0.9802 - loss: 0.0612 - val_accuracy: 0.5750 - val_loss: 4.2690
Epoch 195/200
25/25 ----- 12s 458ms/step - accuracy: 0.9828 - loss: 0.0629 - val_accuracy: 0.5700 - val_loss: 3.7037
Epoch 196/200
25/25 ----- 11s 457ms/step - accuracy: 0.9917 - loss: 0.0292 - val_accuracy: 0.6000 - val_loss: 3.6349
Epoch 197/200
25/25 ----- 11s 457ms/step - accuracy: 0.9881 - loss: 0.0378 - val_accuracy: 0.5800 - val_loss: 3.7407
Epoch 198/200
25/25 ----- 12s 460ms/step - accuracy: 0.9869 - loss: 0.0346 - val_accuracy: 0.5800 - val_loss: 3.9399
Epoch 199/200
25/25 ----- 12s 461ms/step - accuracy: 0.9959 - loss: 0.0230 - val_accuracy: 0.5700 - val_loss: 4.6127
Epoch 200/200
25/25 ----- 12s 467ms/step - accuracy: 0.9954 - loss: 0.0106 - val_accuracy: 0.5800 - val_loss: 4.2340

```

```
In [8]: print(f"Execution time: {elapsed_time:.2f} seconds")
```

Execution time: 2385.14 seconds

```
In [9]: def append_core_data(score_path, num_cores, elapsed_time):
        # Check if the file already exists
        file_exists = os.path.exists(score_path)

        # Open the file in append mode
        with open(score_path, mode='a', newline='') as file:
```



```
writer = csv.writer(file)

# If the file is new, write the header
if not file_exists:
    writer.writerow(["Number of Cores", "Elapsed Time"])

# Write the new data
writer.writerow([num_cores, elapsed_time])
```

```
In [10]: score_path = r"C:\Users\nikhi\OneDrive\Desktop\Final Project\DEEP LEARNING WITH HPSC\core_data.txt"
append_core_data(score_path, number_of_worker, elapsed_time)
```